Notebooks are still at: https://github.com/minrk/ipython-cse17

Or follow along on JupyterHub at https://cse17.jupyter.org

# **Profiling and Optimising**

IPython provides some tools for making it a bit easier to profile and optimise your code.

Help

```
In []: %matplotlib inline
    import numpy as np
    import matplotlib.pyplot as plt

In []: try:
        import seaborn as sns
    except ImportError:
        print("That's okay")
```

## %timeit

The main IPython tool we are going to use here is %timeit, a magic that automates measuring how long it



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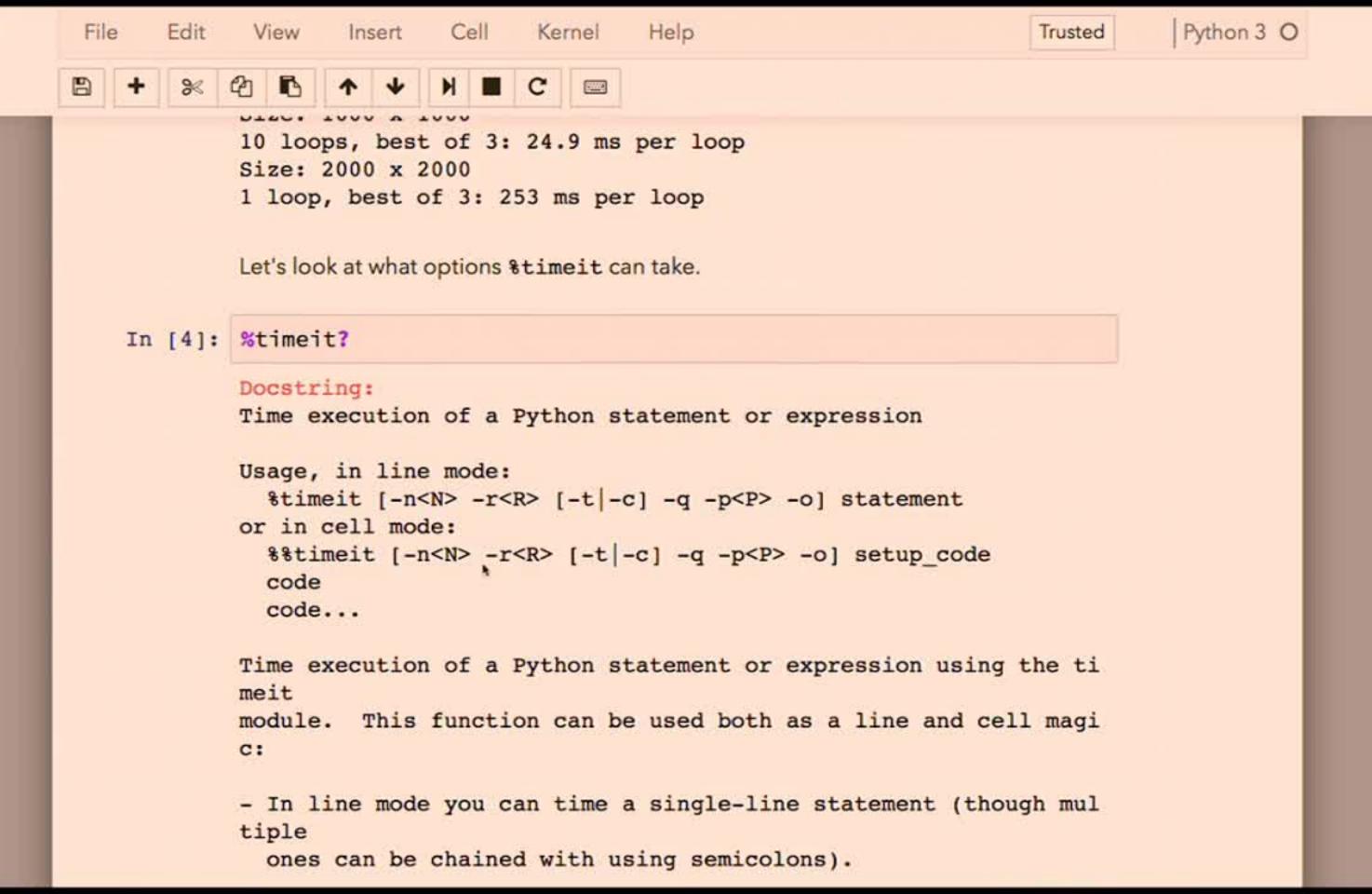
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Insert

Cell

View

Edit

File

%timeit [-n<N> -r<R> [-t|-c] -q -p<P> -o] statement
or in cell mode:
 %%timeit [-n<N> -r<R> [-t|-c] -q -p<P> -o] setup\_code
 code
 code...

Kernel

Time execution of a Python statement or expression using the ti meit module. This function can be used both as a line and cell magi

Help

c:

- In line mode you can time a single-line statement (though mul tiple ones can be chained with using semicolons).
- In cell mode, the statement in the first line is used as setu p code

(executed but not timed) and the body of the cell is timed. The cell

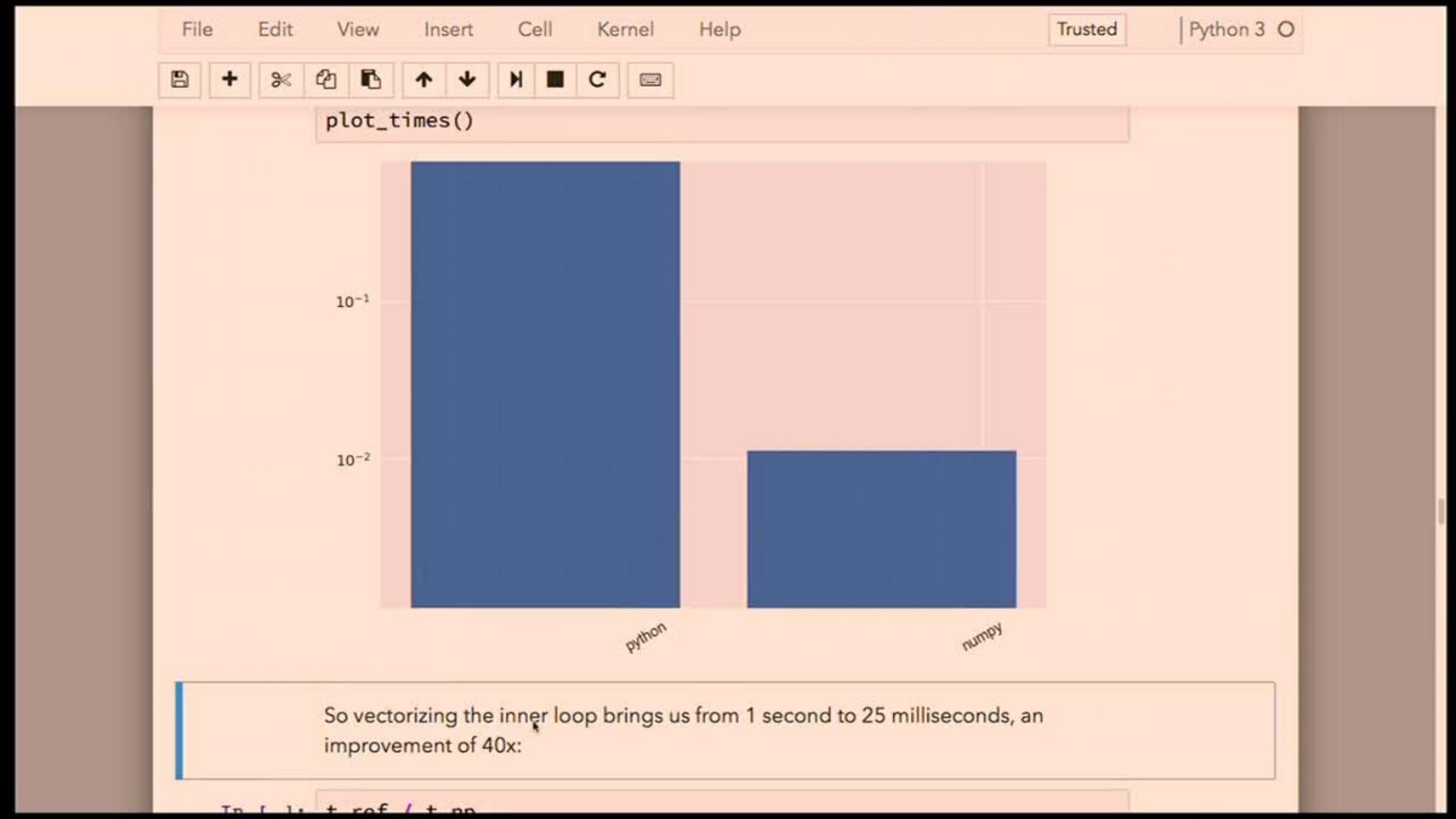
body has access to any variables created in the setup code.

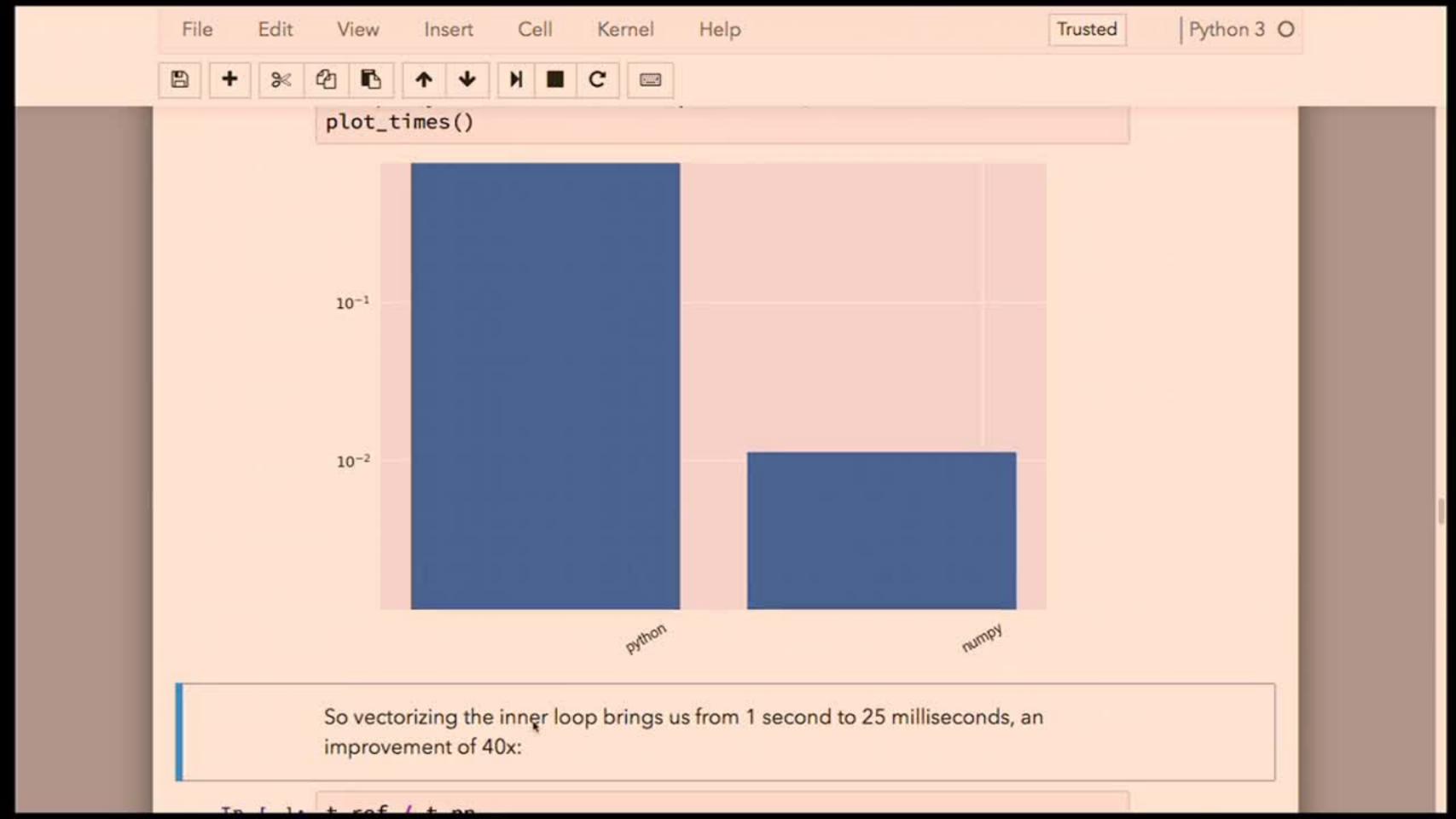
### Options:

-n<N>: execute the given statement <N> times in a loop. If this value is not given, a fitting value is chosen.

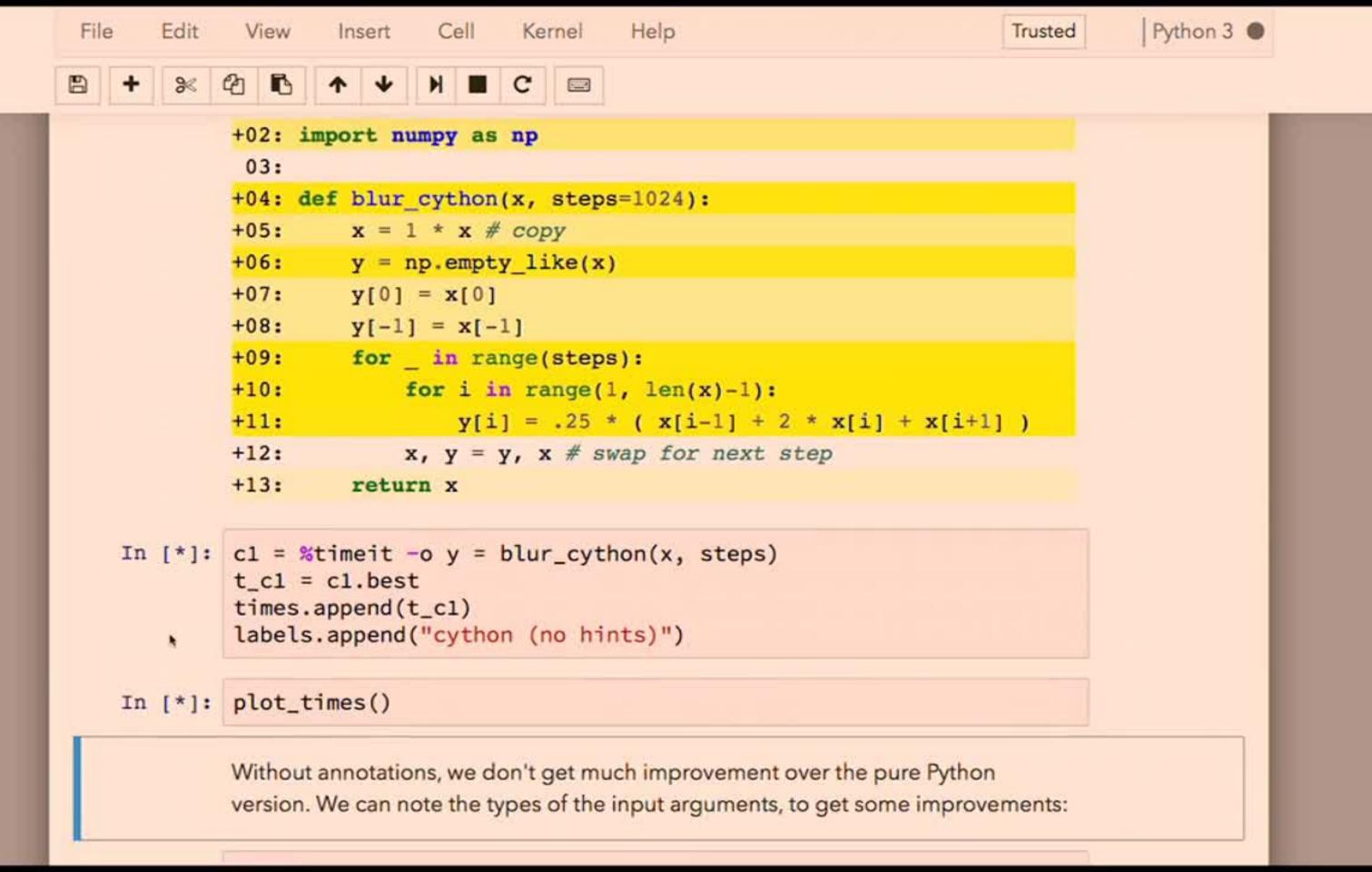
-r<R>: repeat the loop iteration <R> times and take the best re

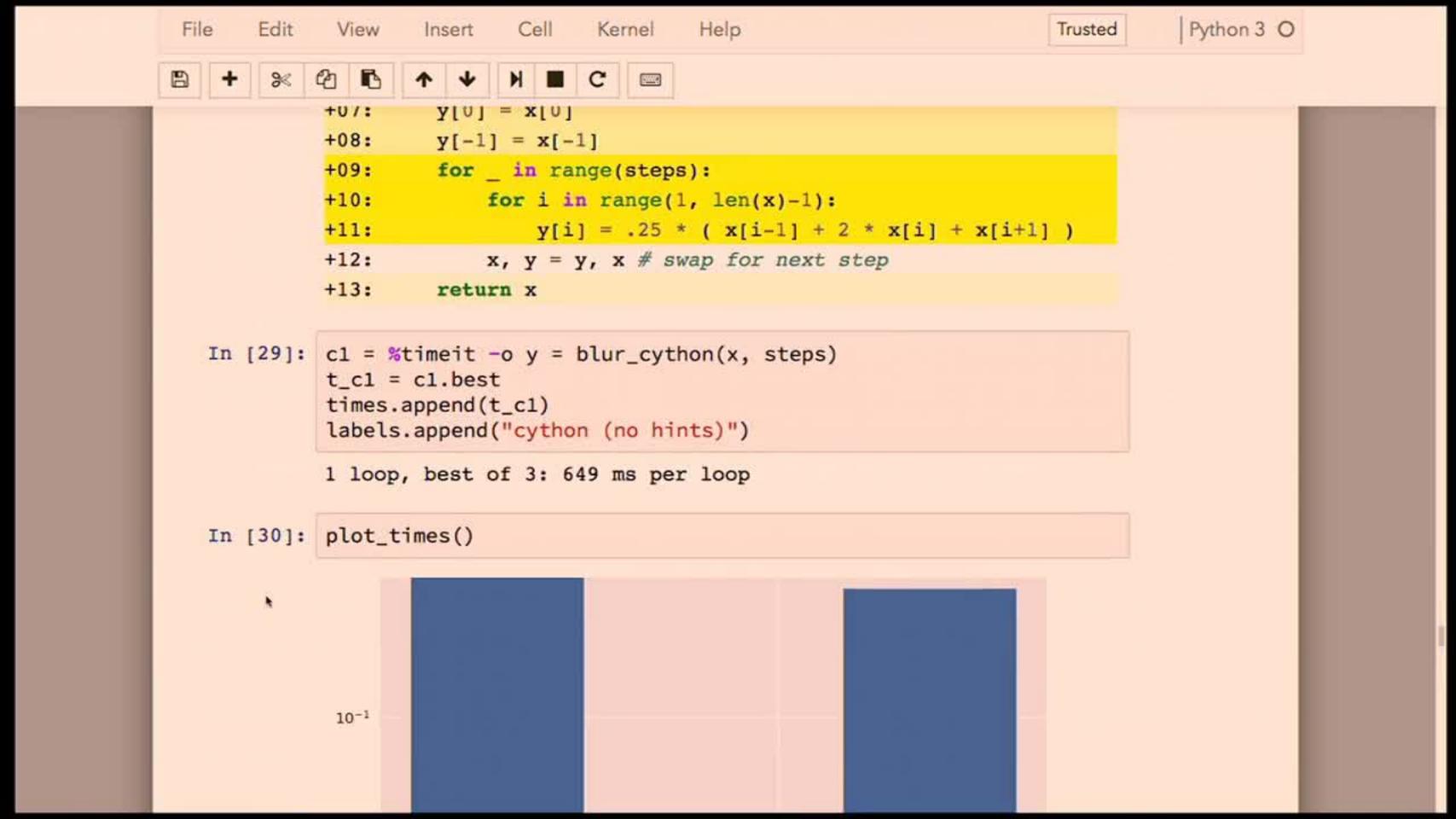














```
In [*]: c2 = %timeit -o blur_cython2(x, steps)
    t_c2 = c2.best
    times.append(t_c2)
    labels.append("cython (loops)")
    plot_times()
```

x, y = y, x # swap for next step

+14:

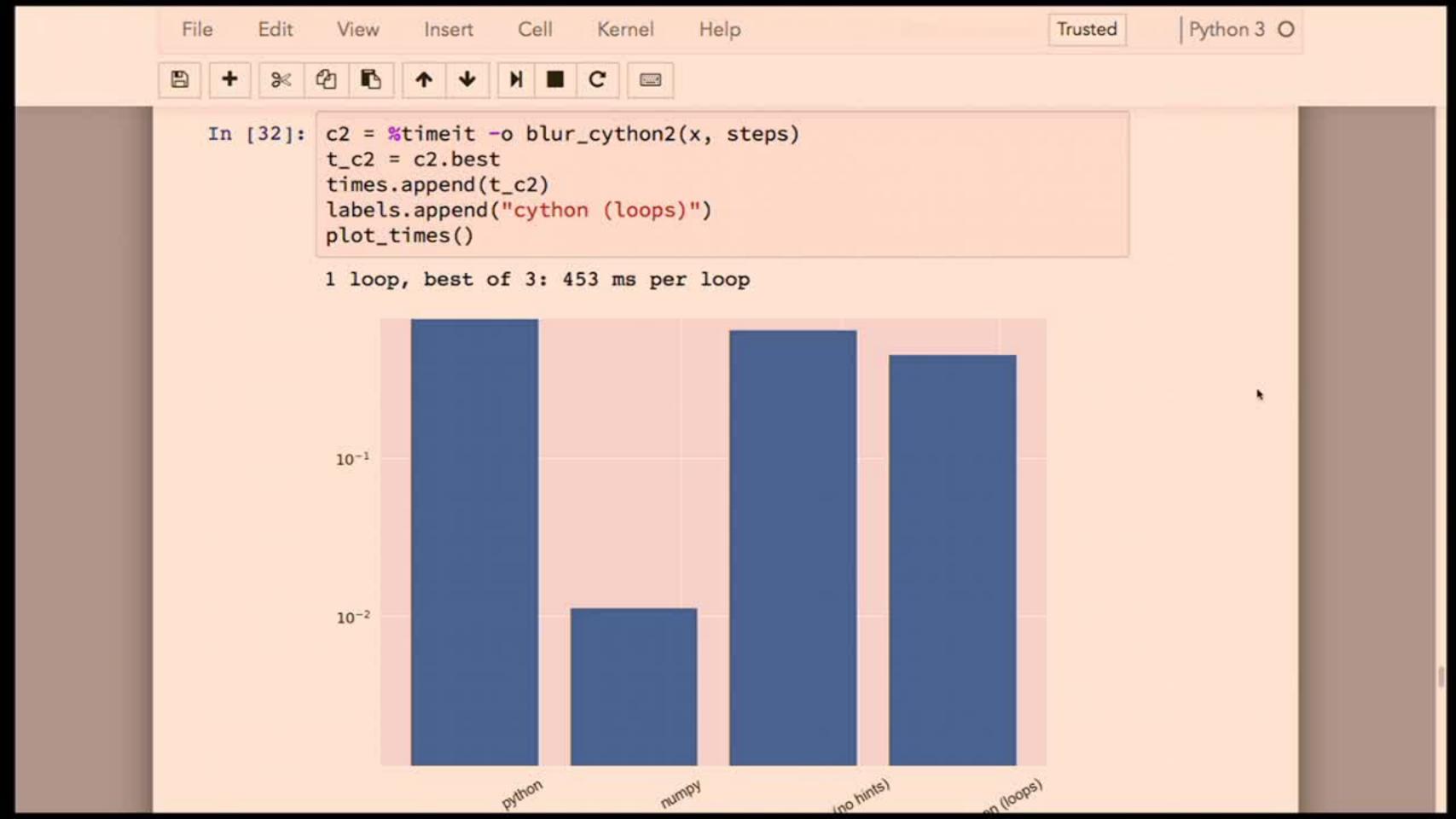
+15:

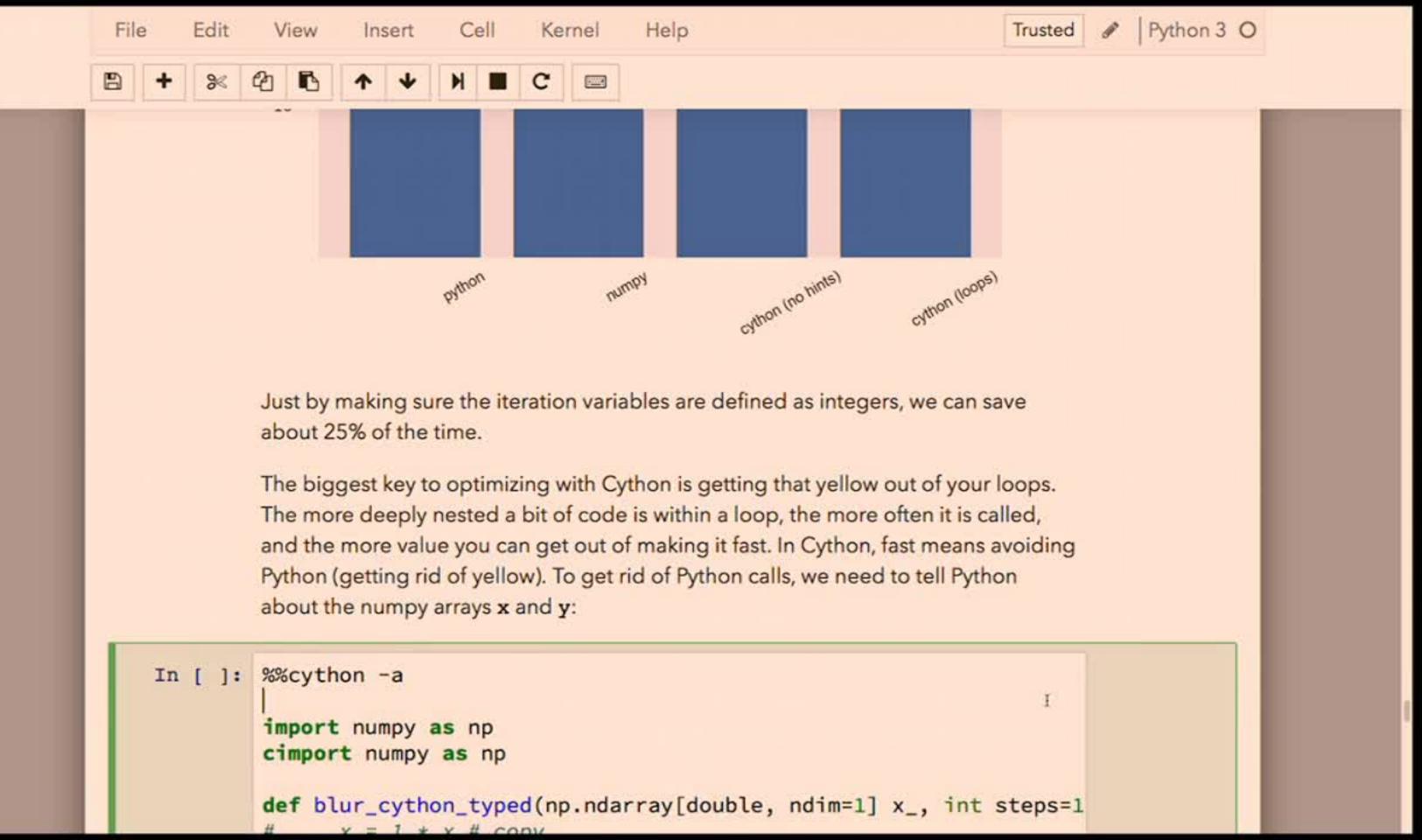
return x

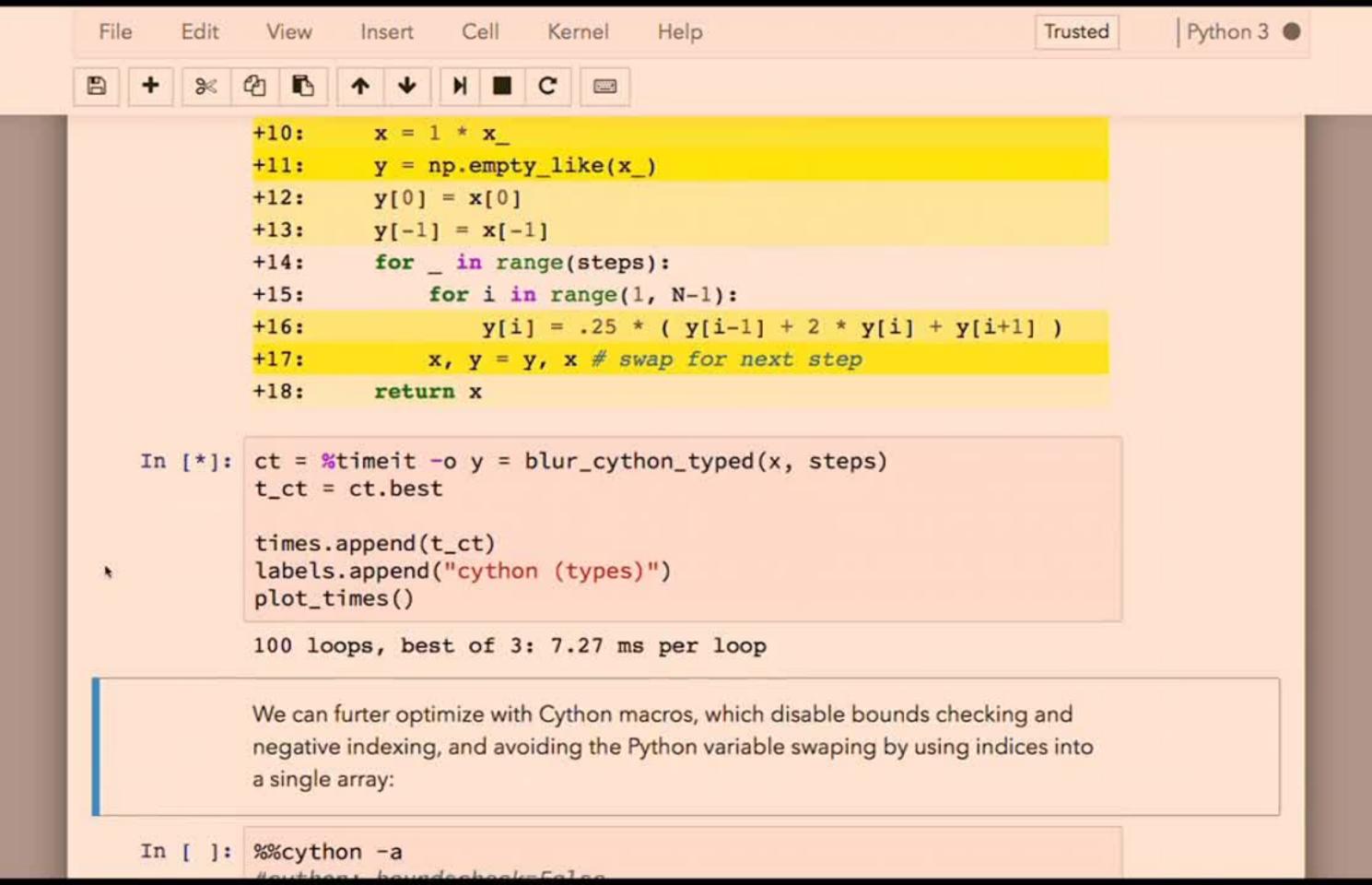
Just by making sure the iteration variables are defined as integers, we can save about 25% of the time.

The biggest key to optimizing with Cython is getting that yellow out of your loops.

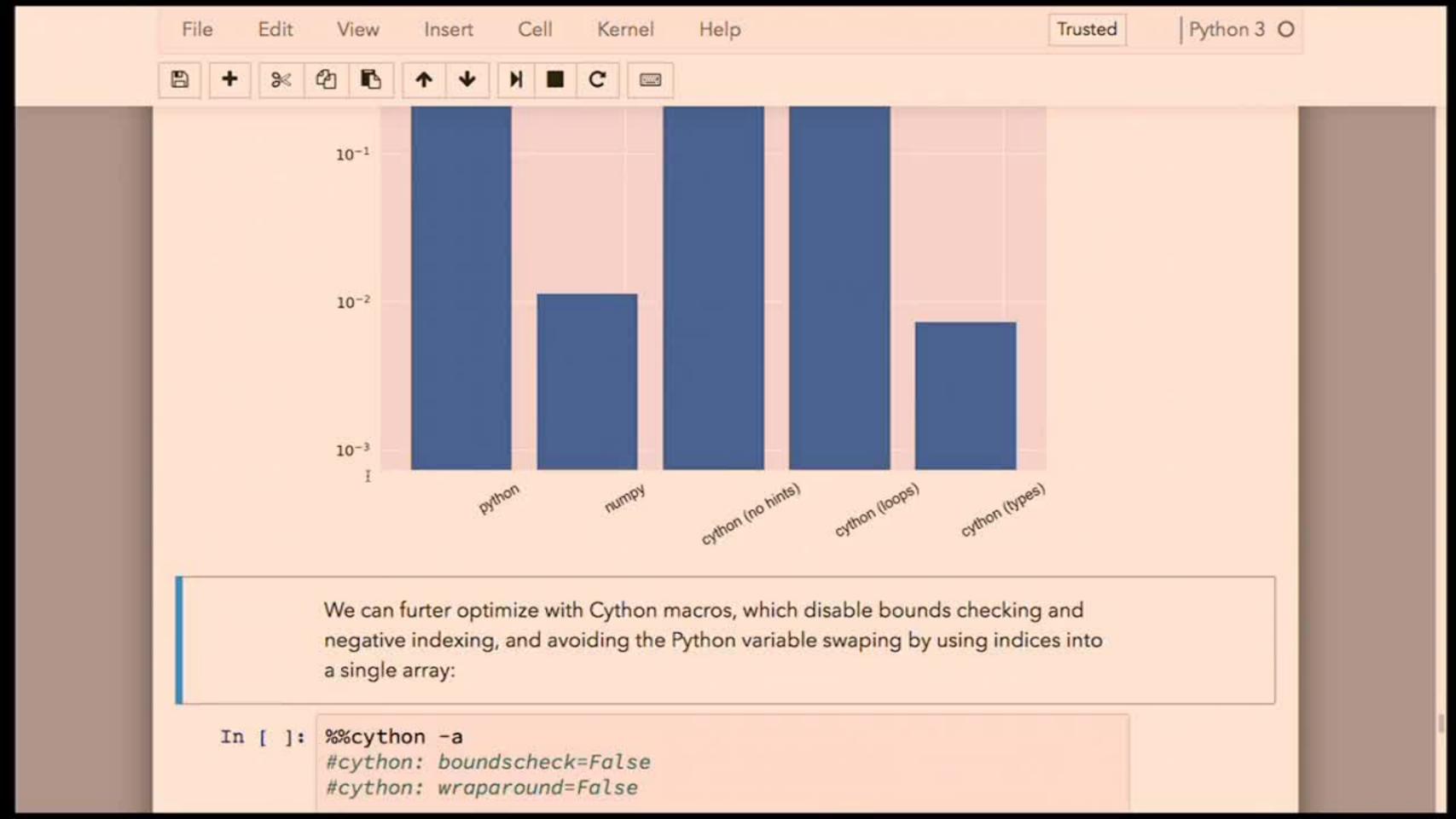
The more deeply nested a bit of code is within a loop, the more often it is called, and the more value you can get out of making it fast. In Cython, fast means avoiding Python (getting rid of yellow). To get rid of Python calls, we need to tell Python about the numpy arrays x and y:

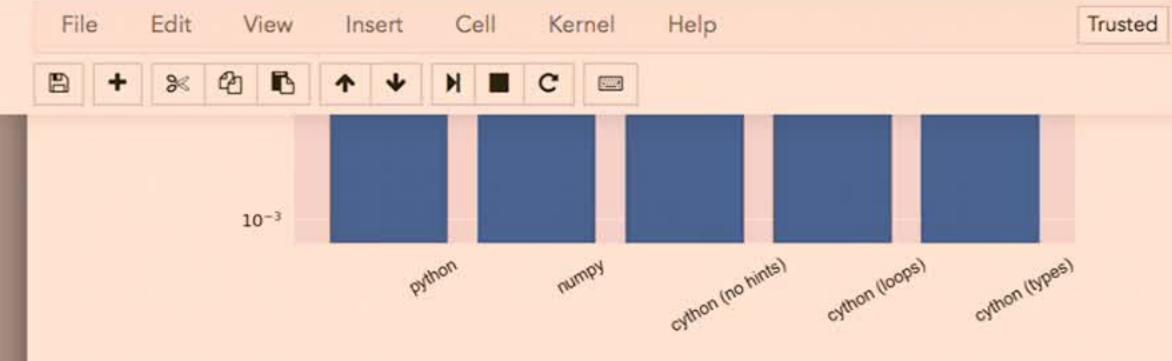






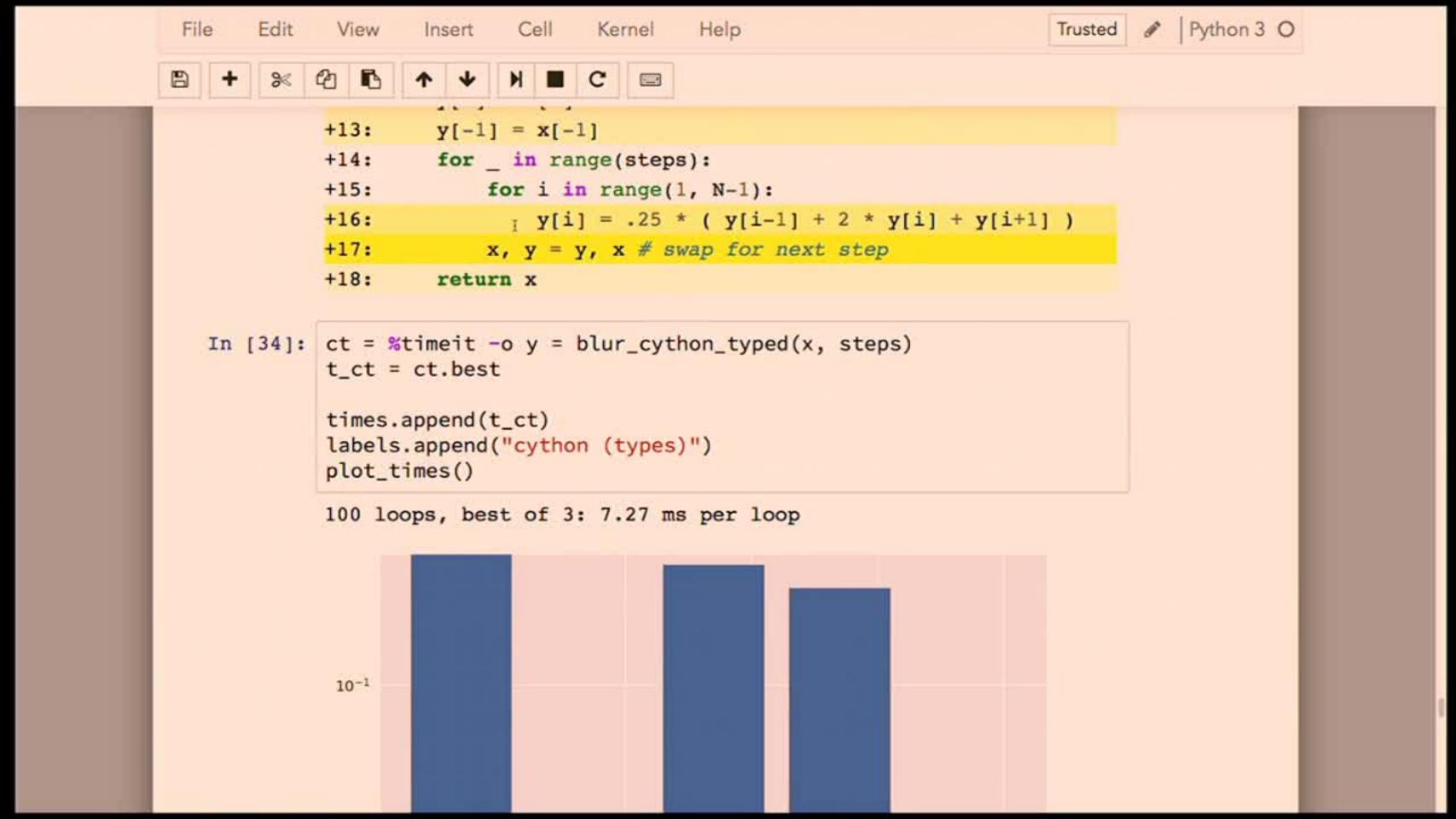




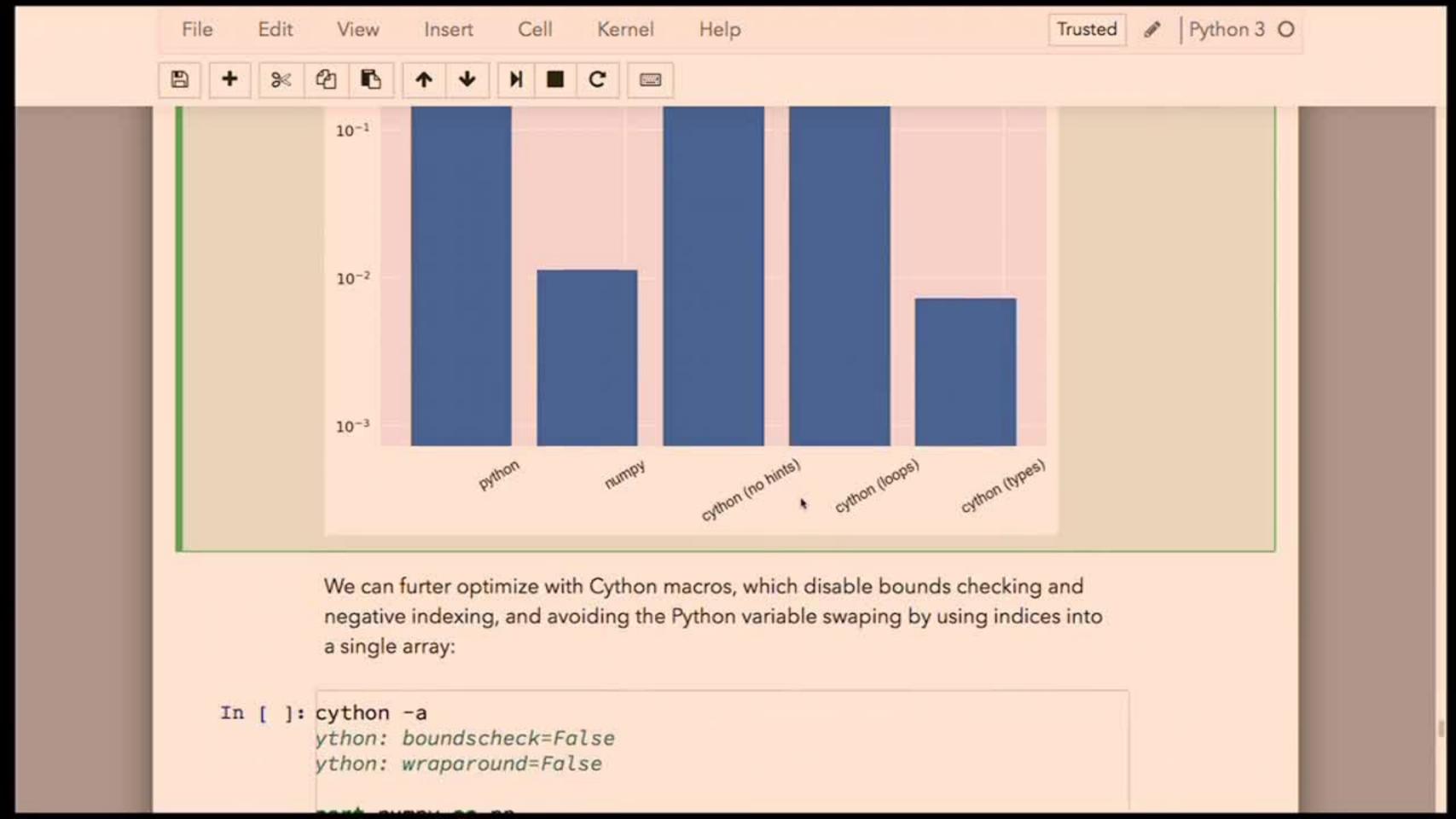


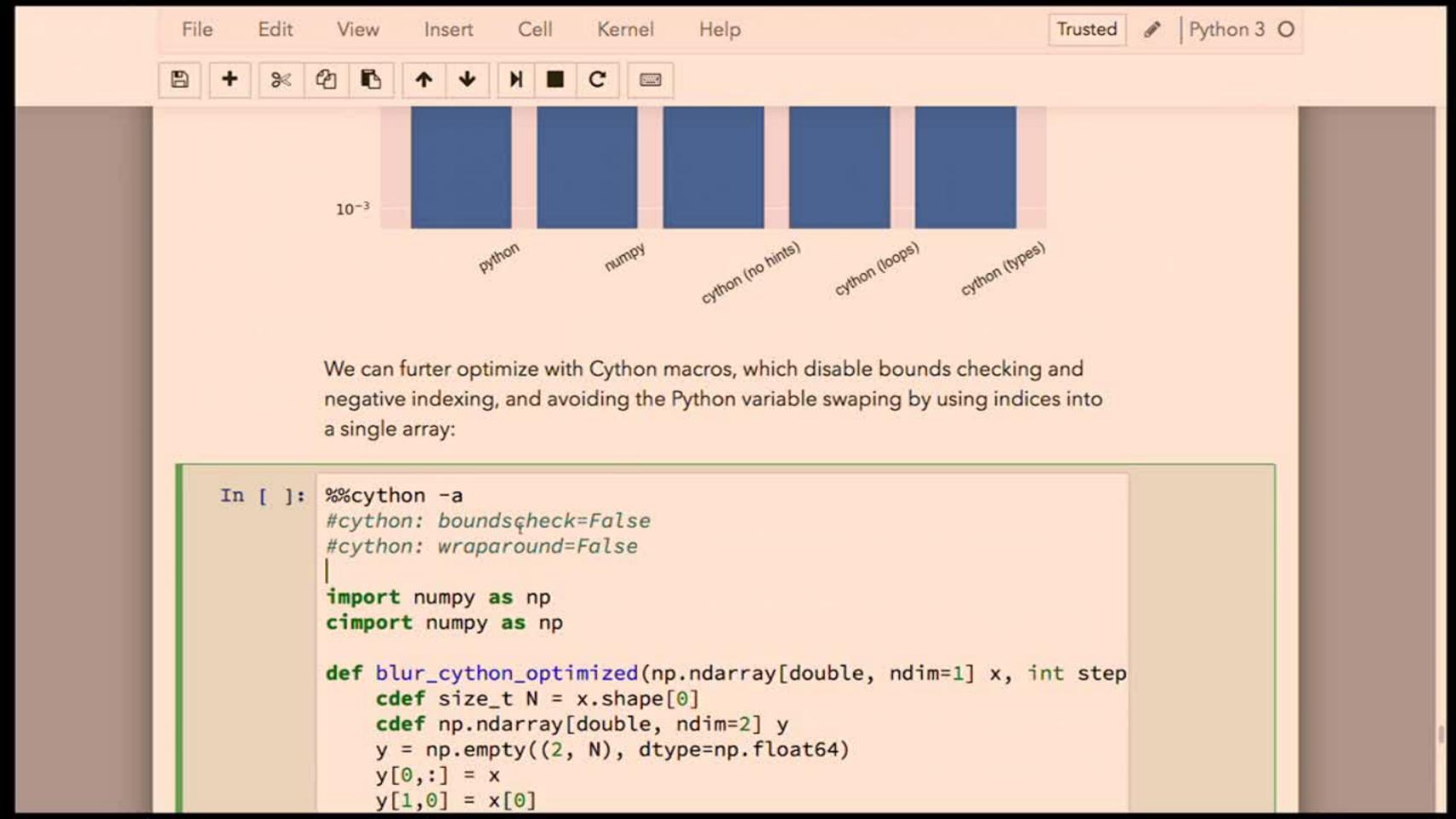
We can furter optimize with Cython macros, which disable bounds checking and negative indexing, and avoiding the Python variable swaping by using indices into a single array:

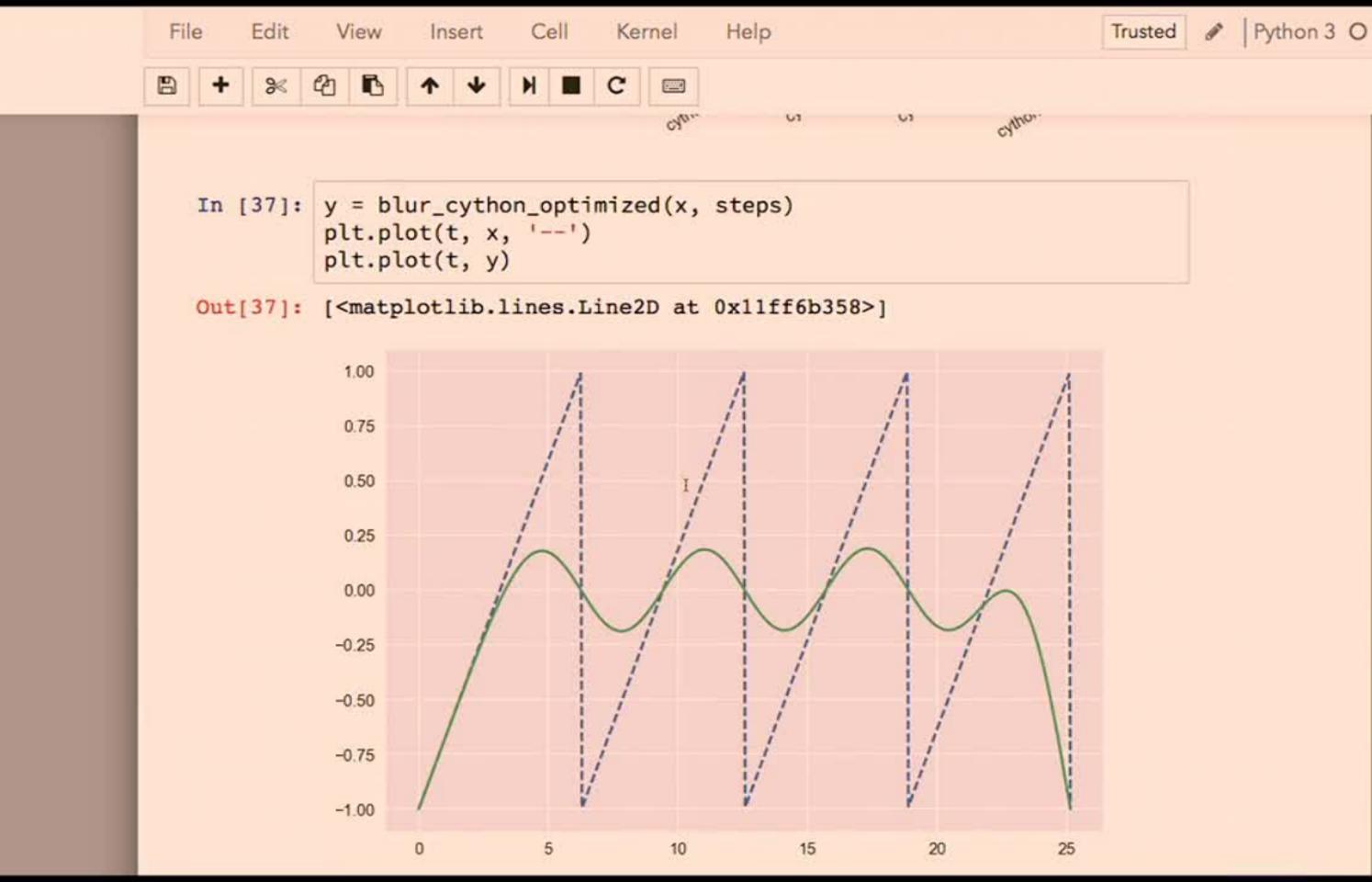
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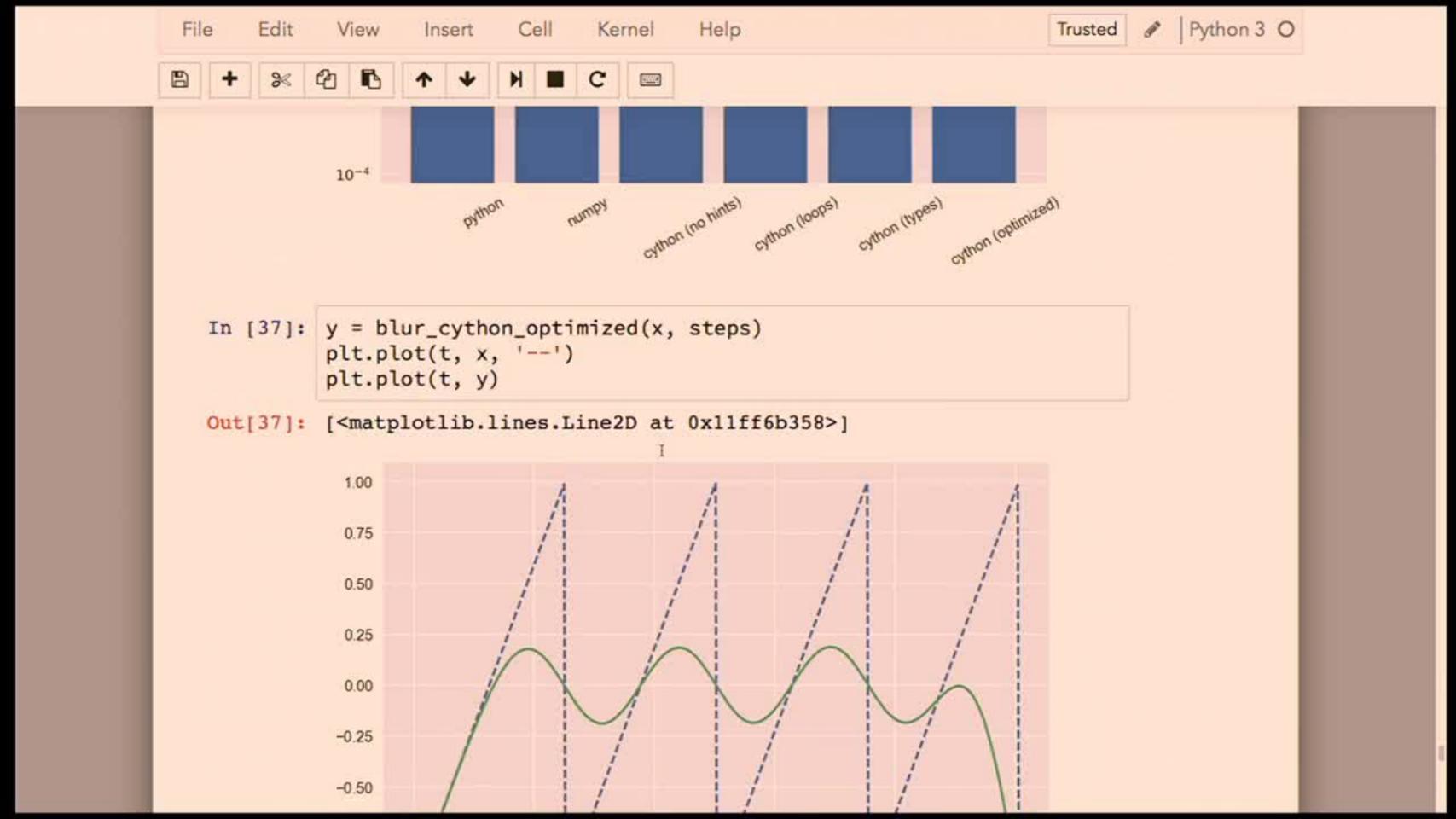


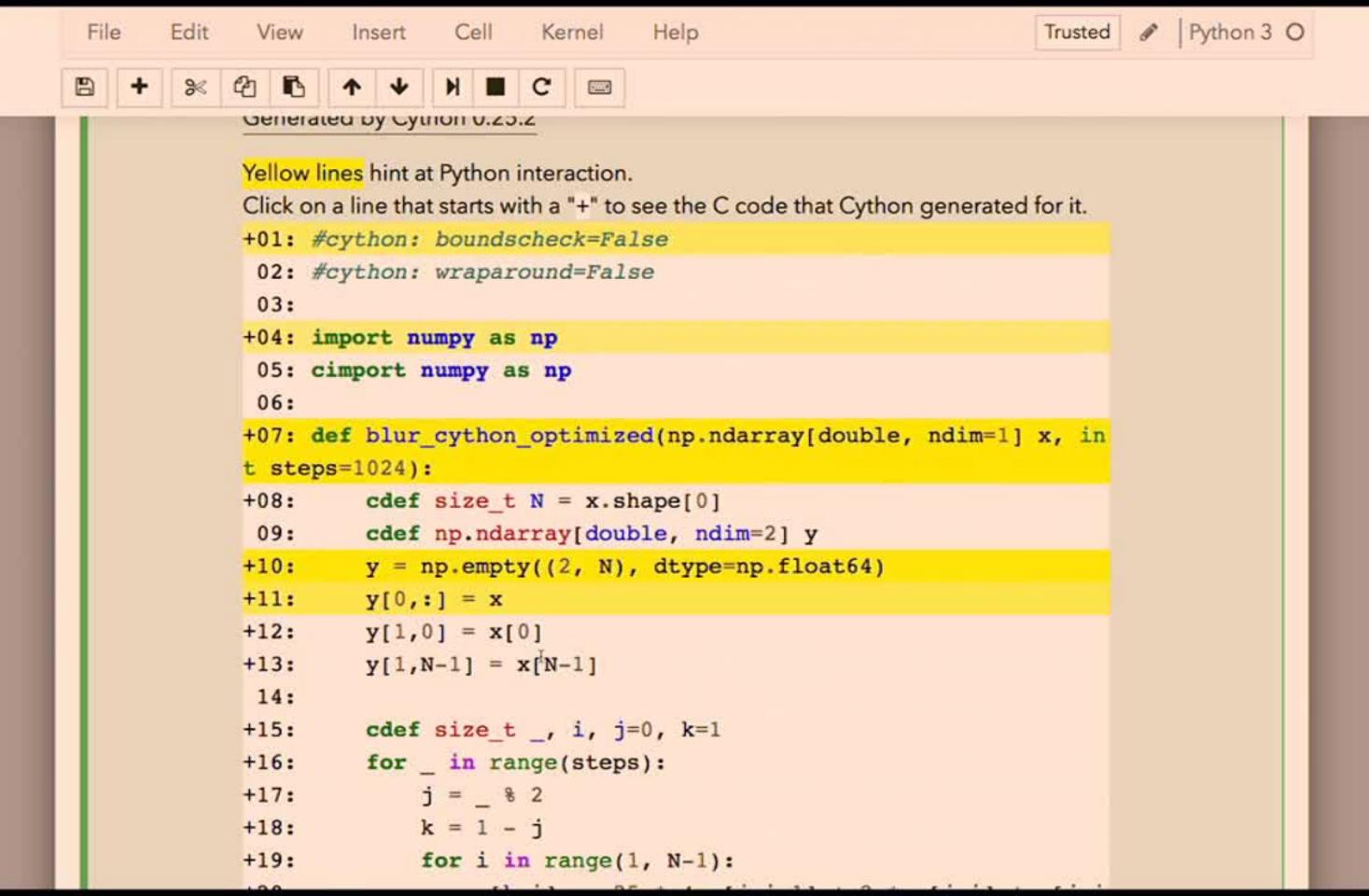


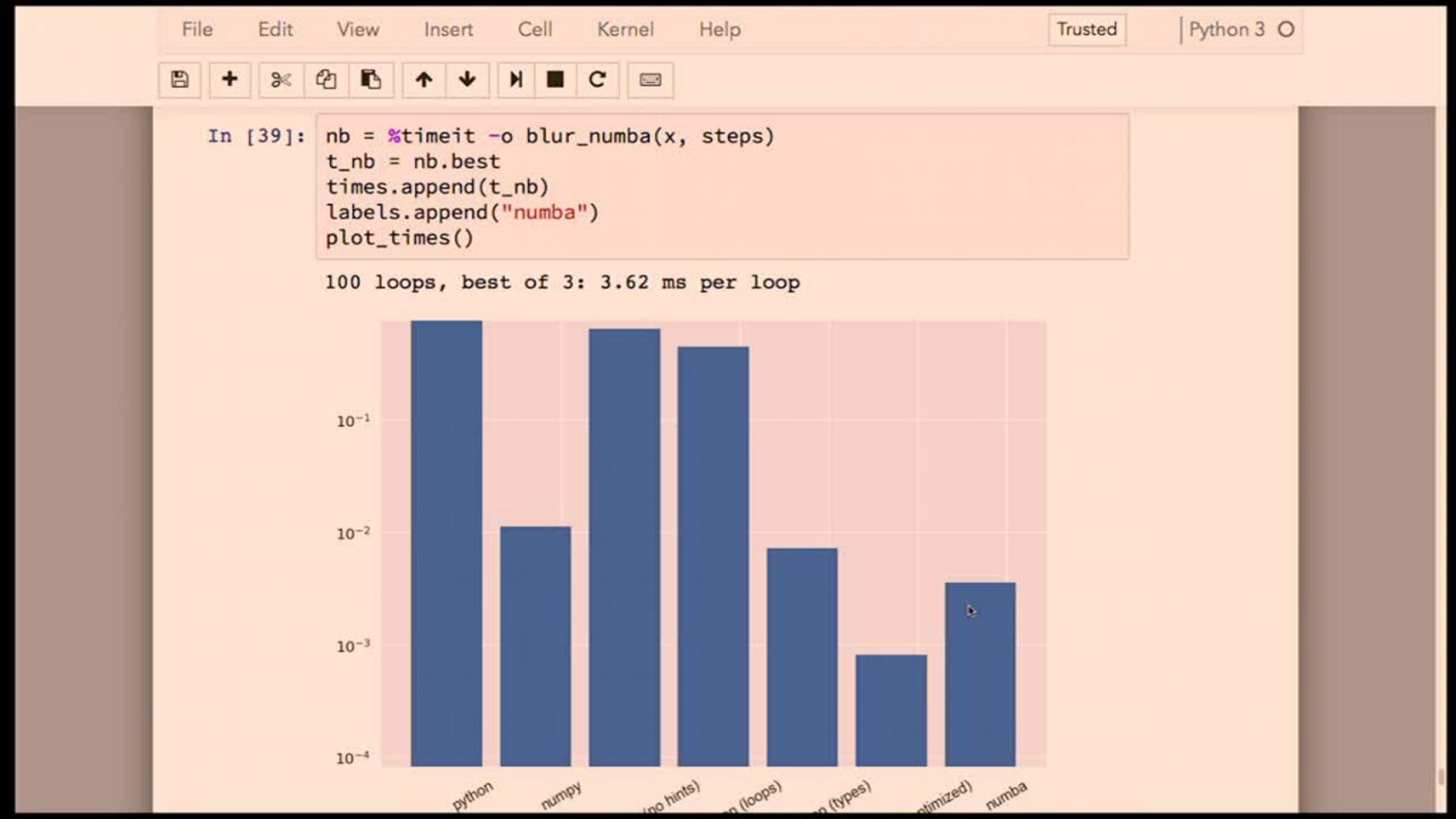


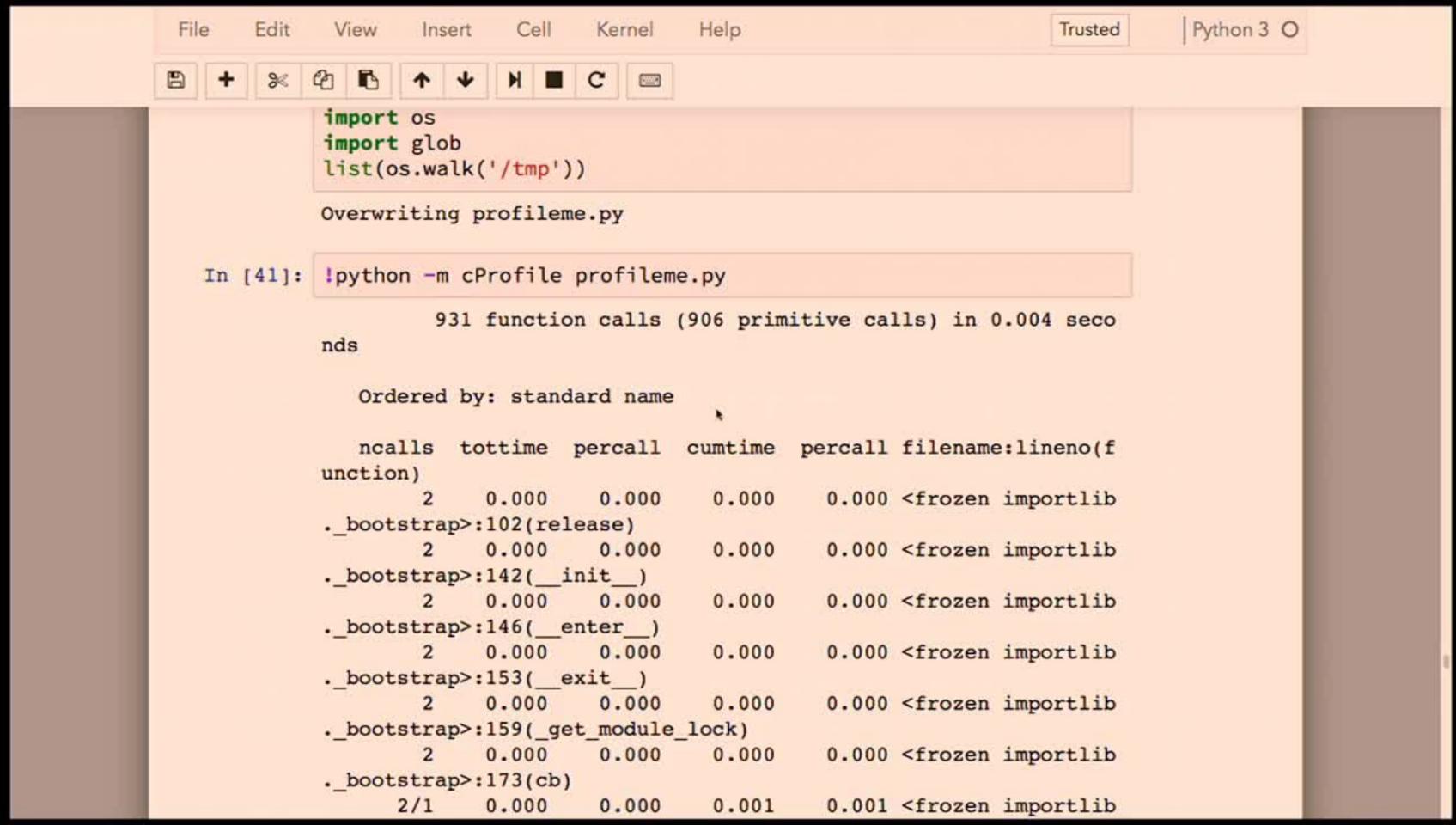


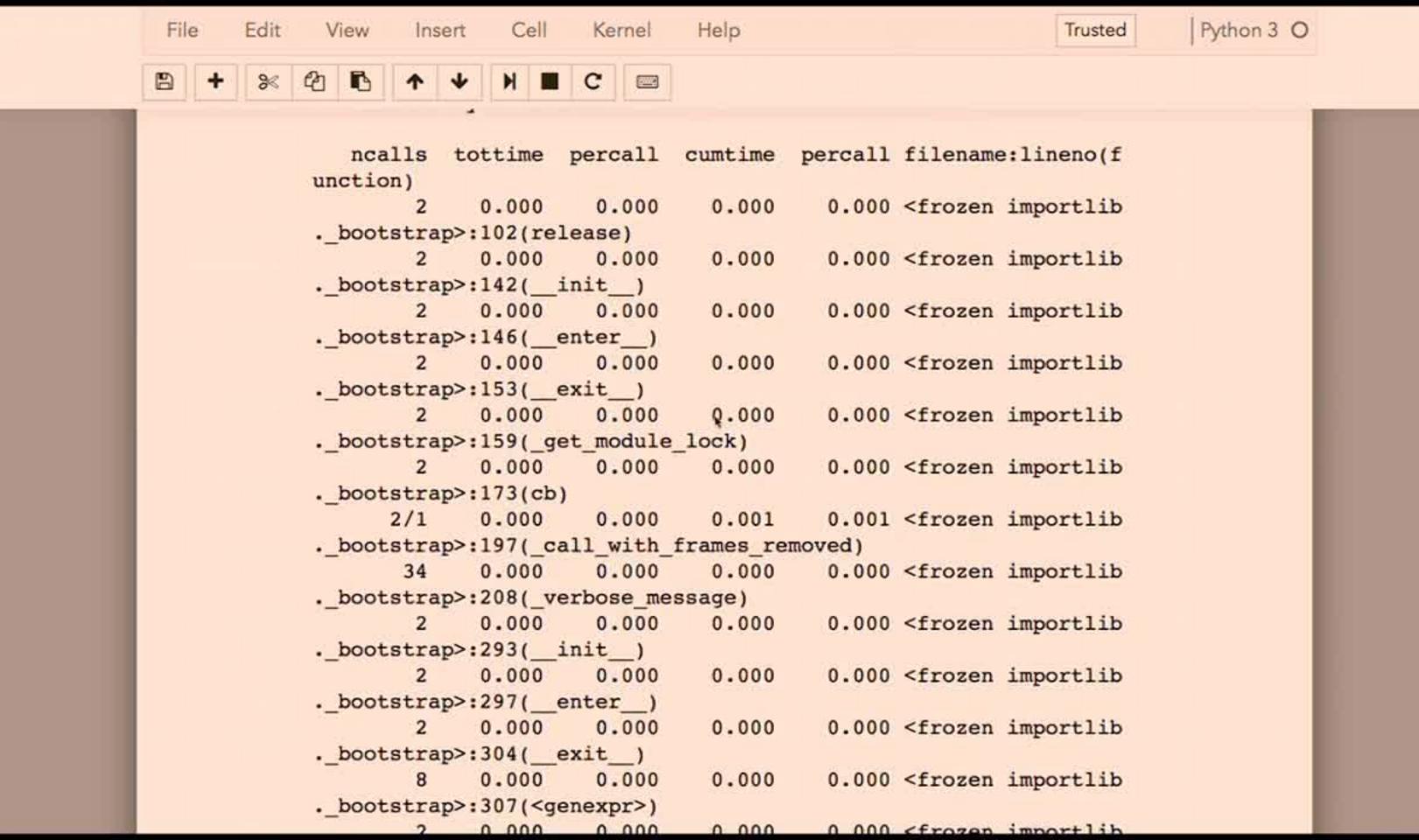


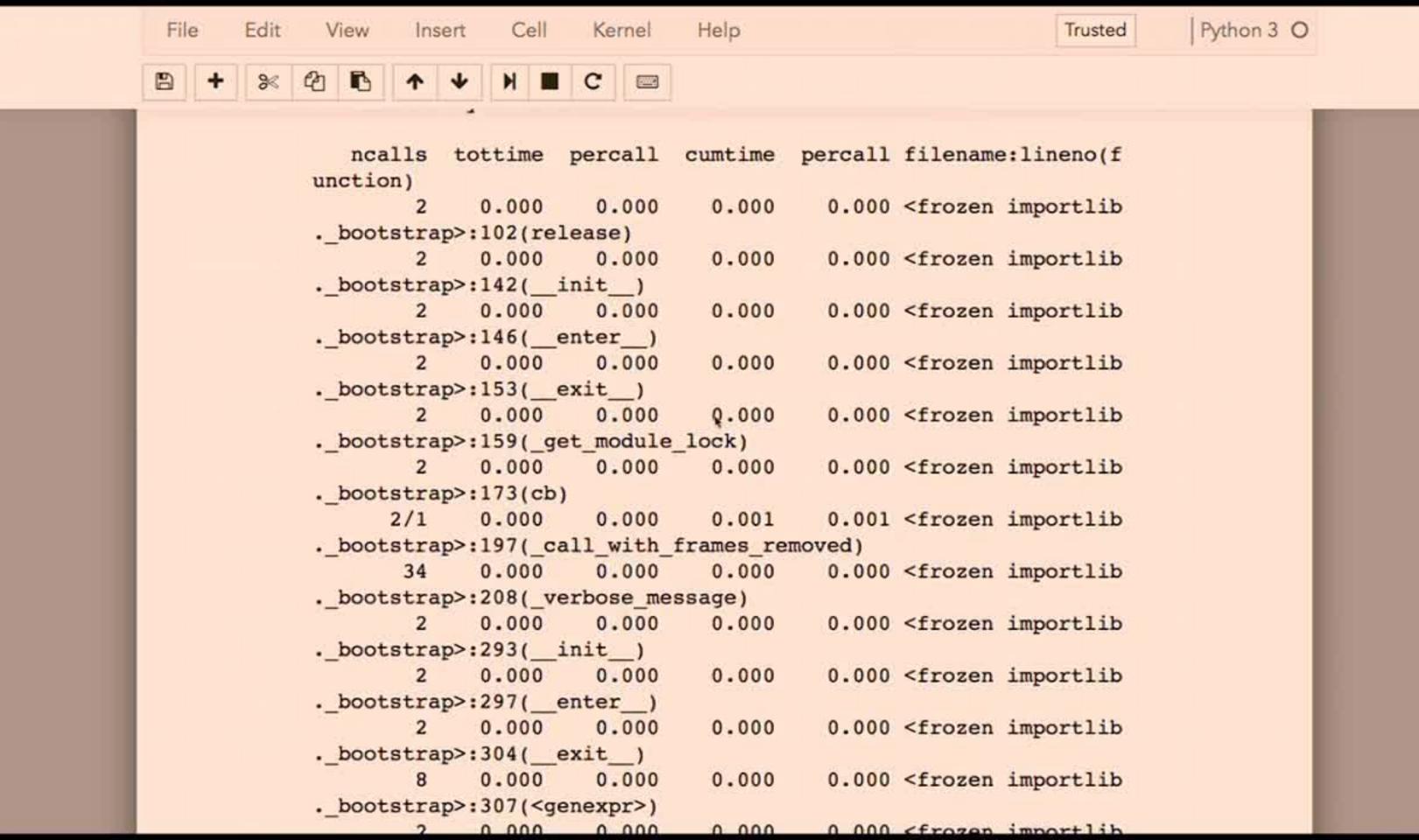


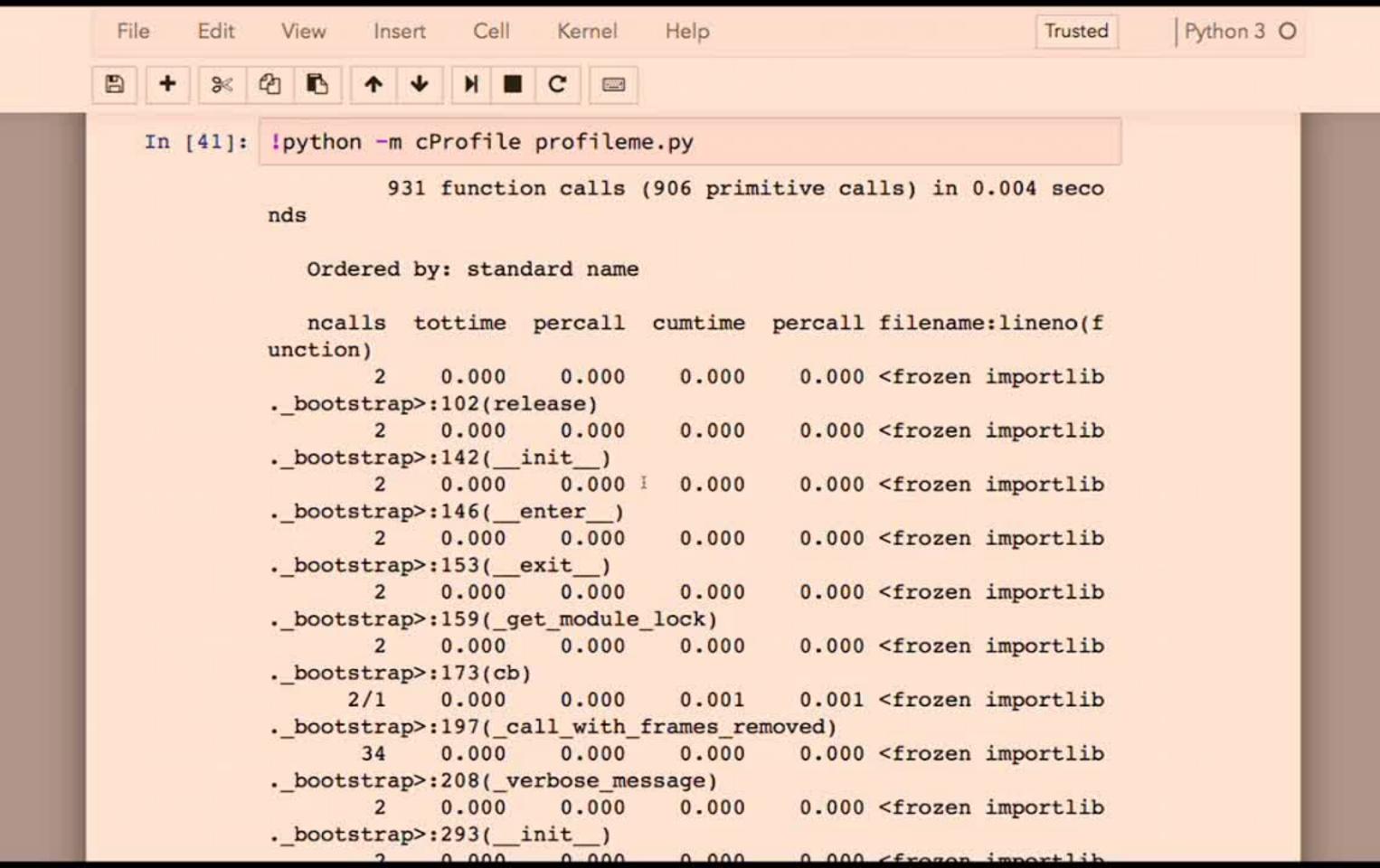


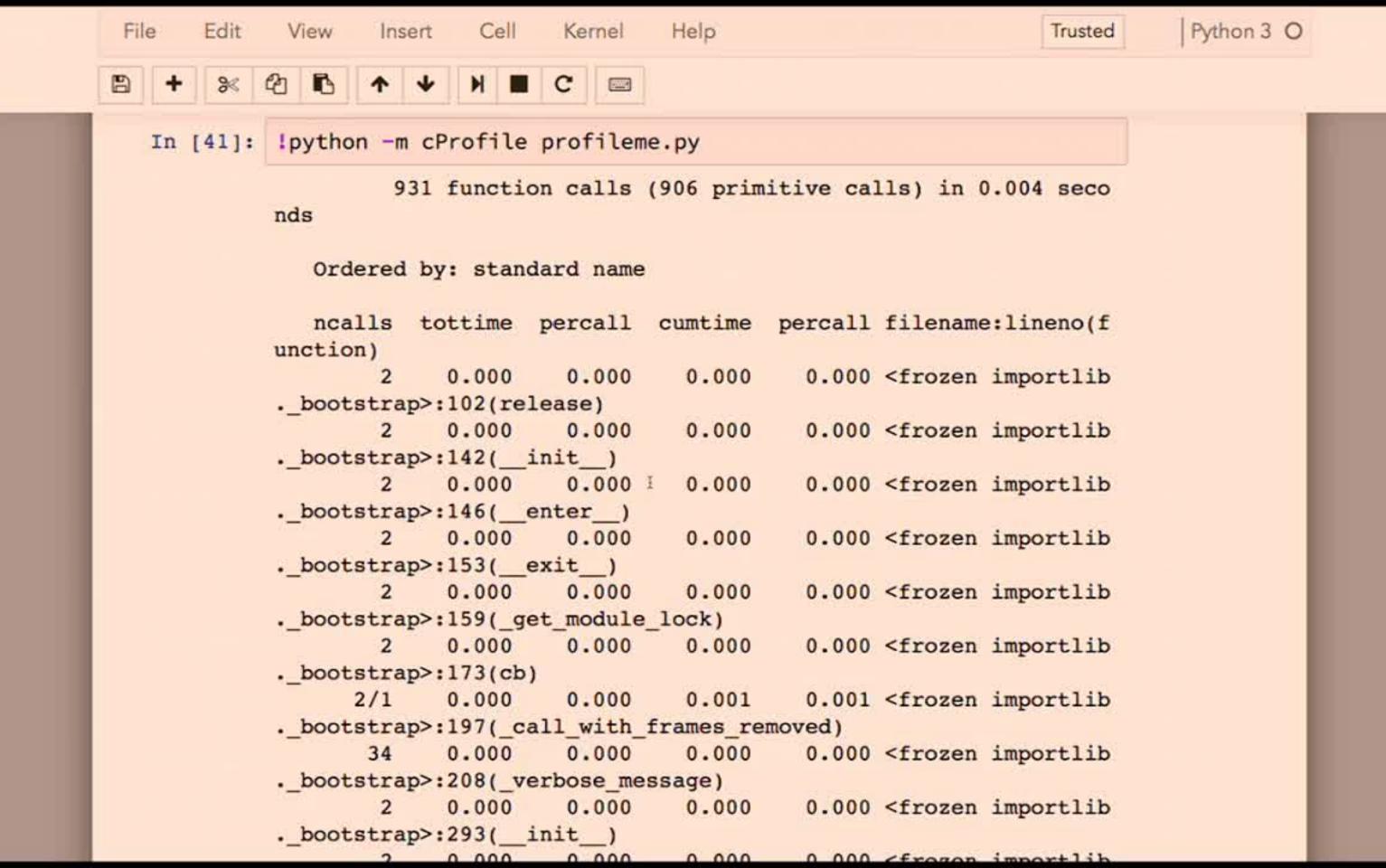


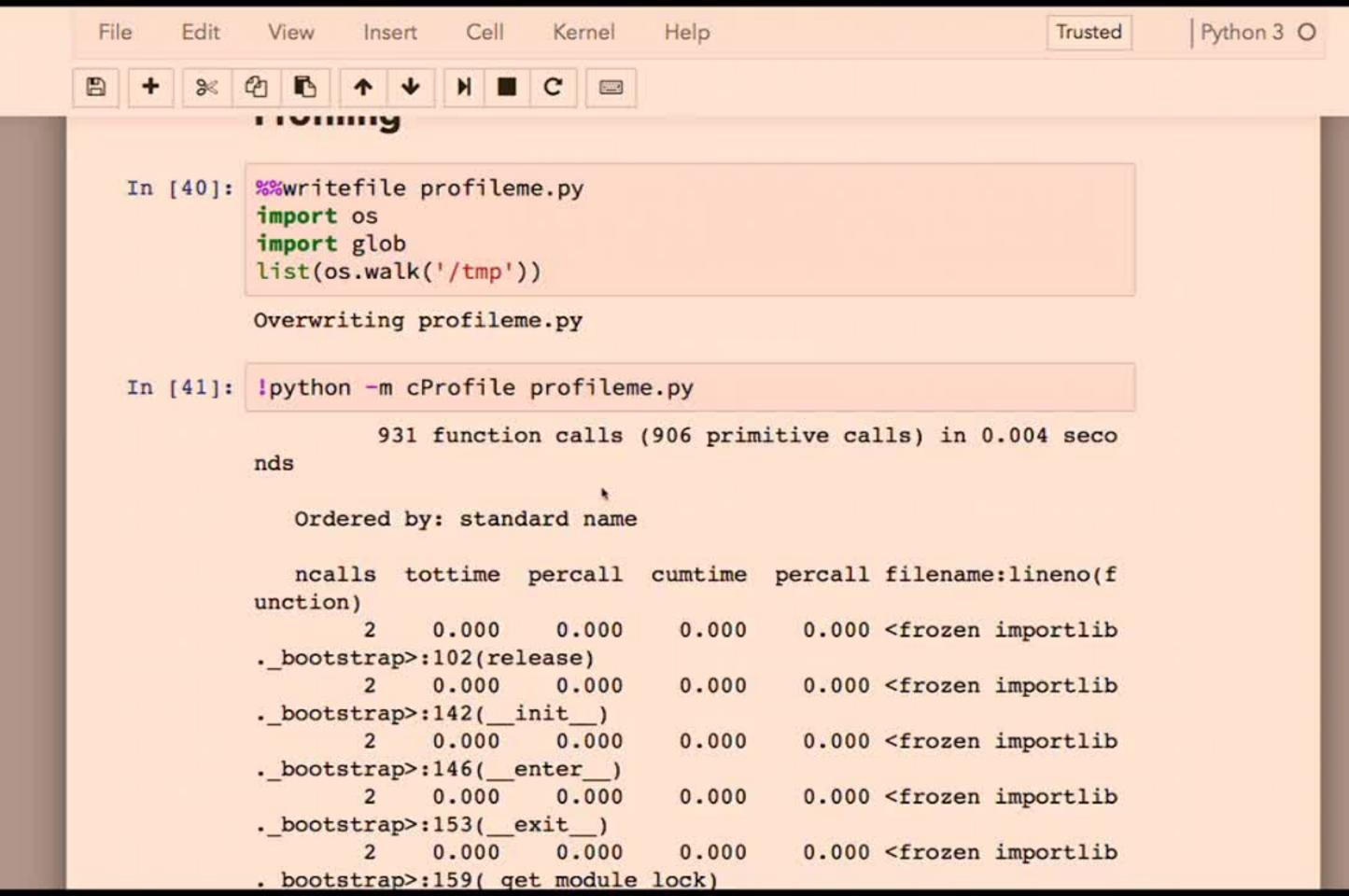


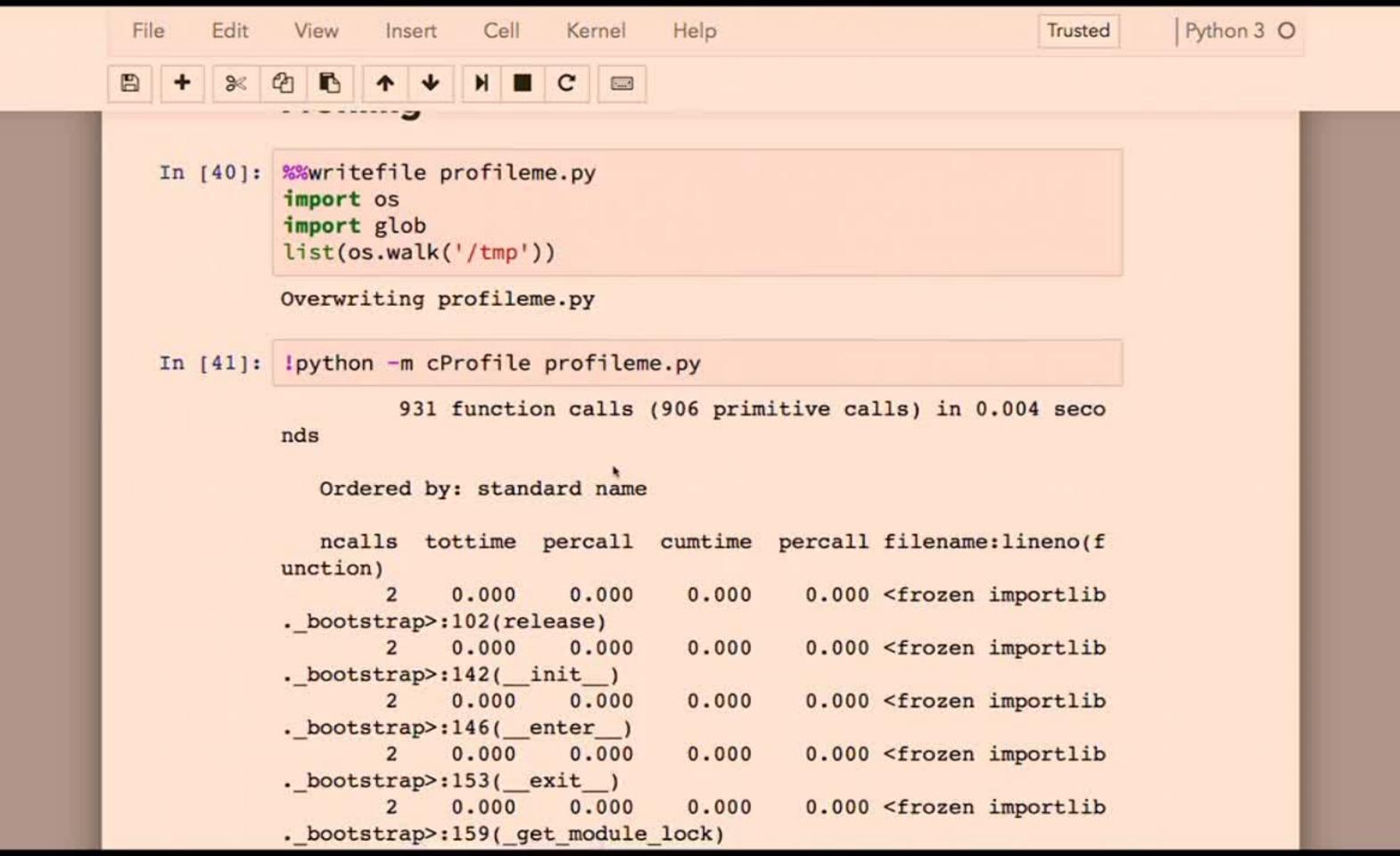


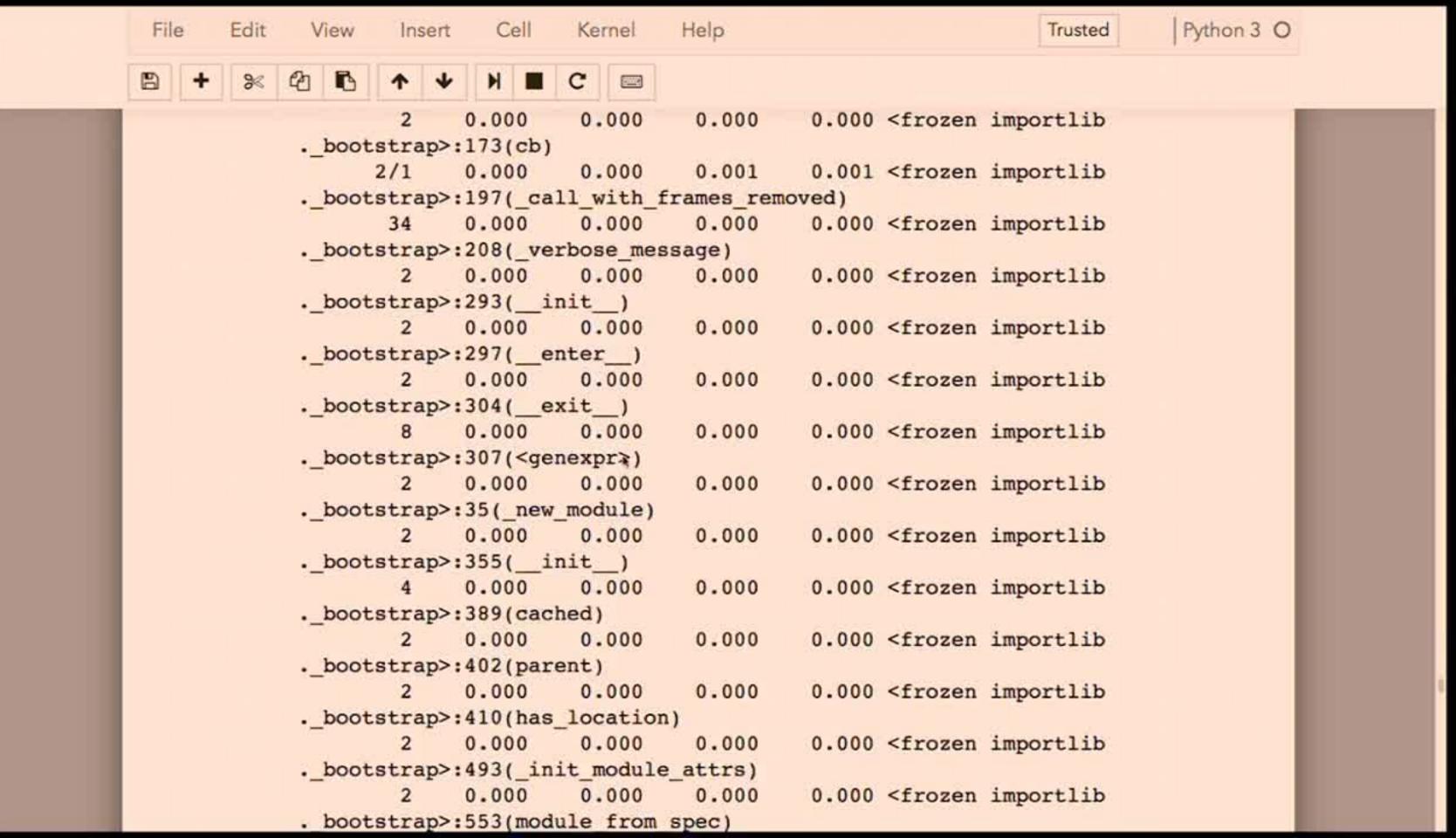


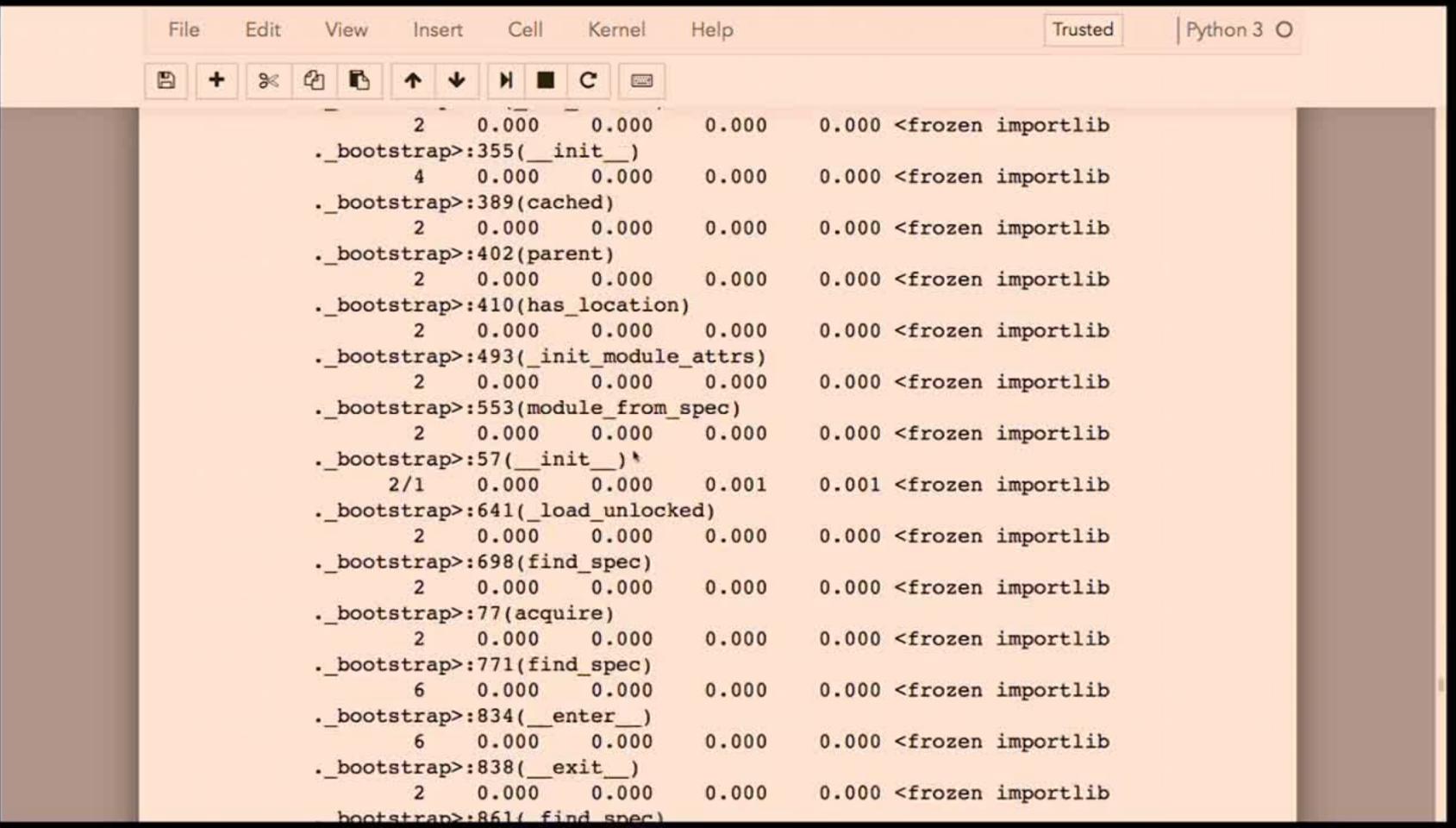


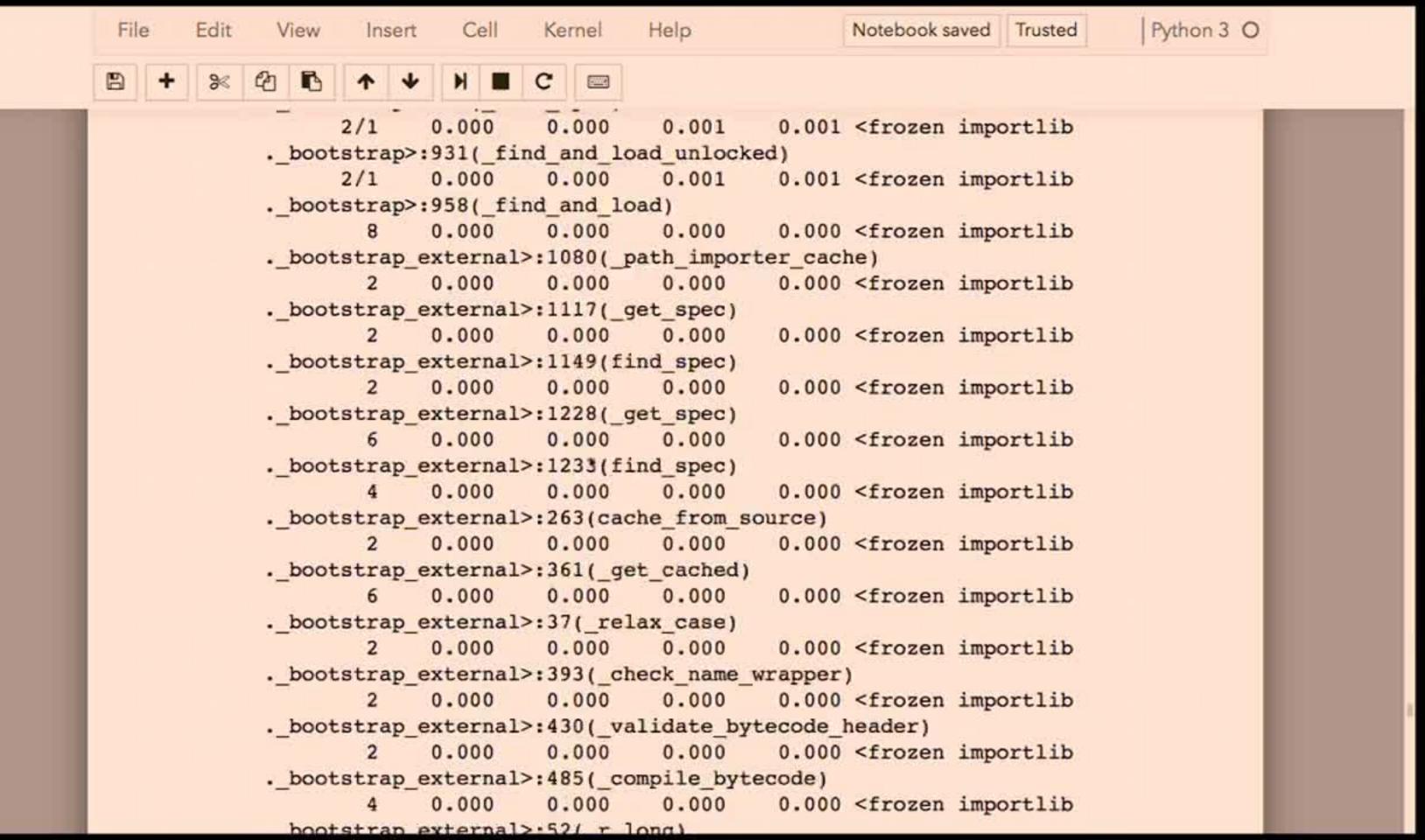


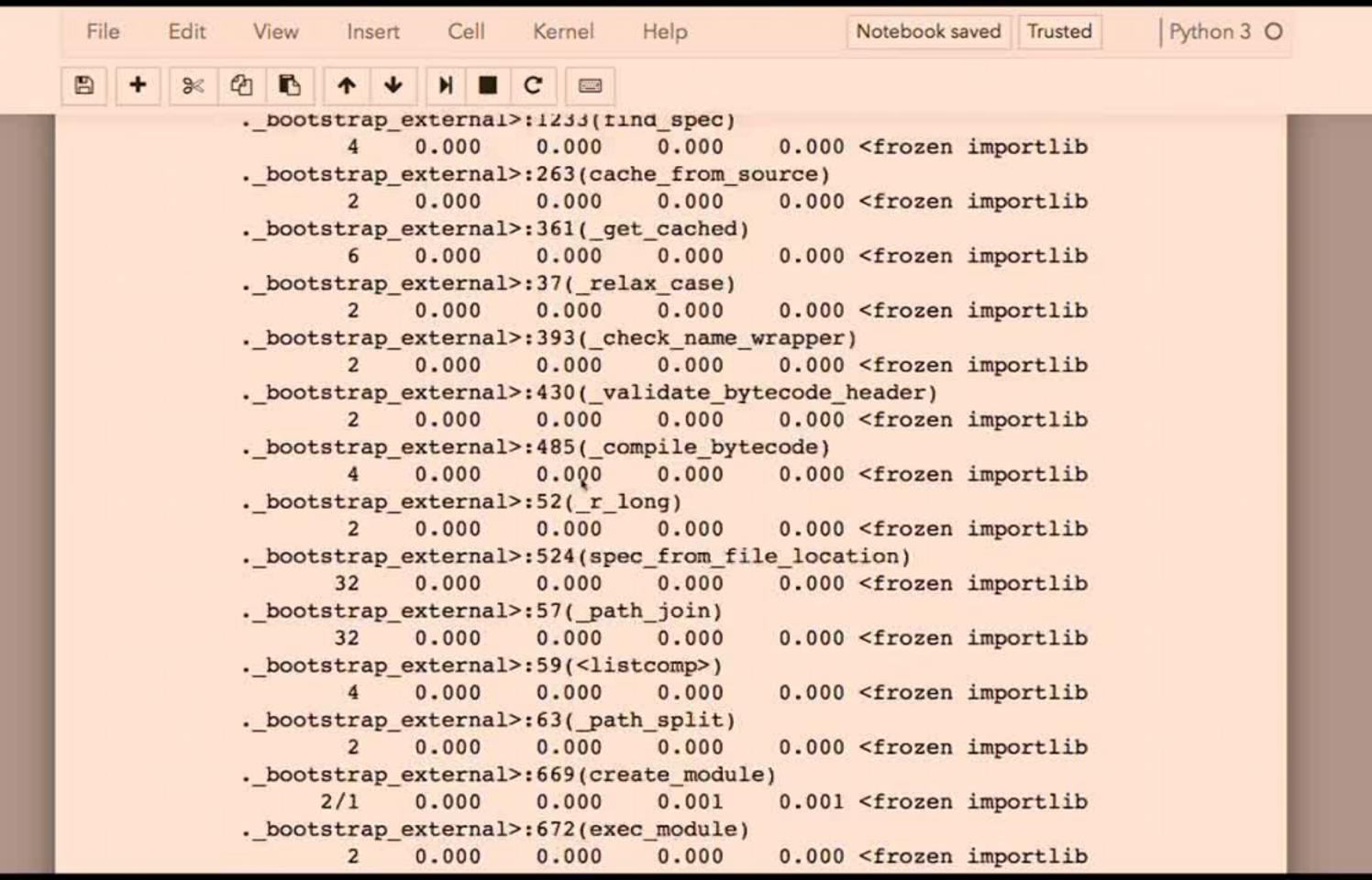


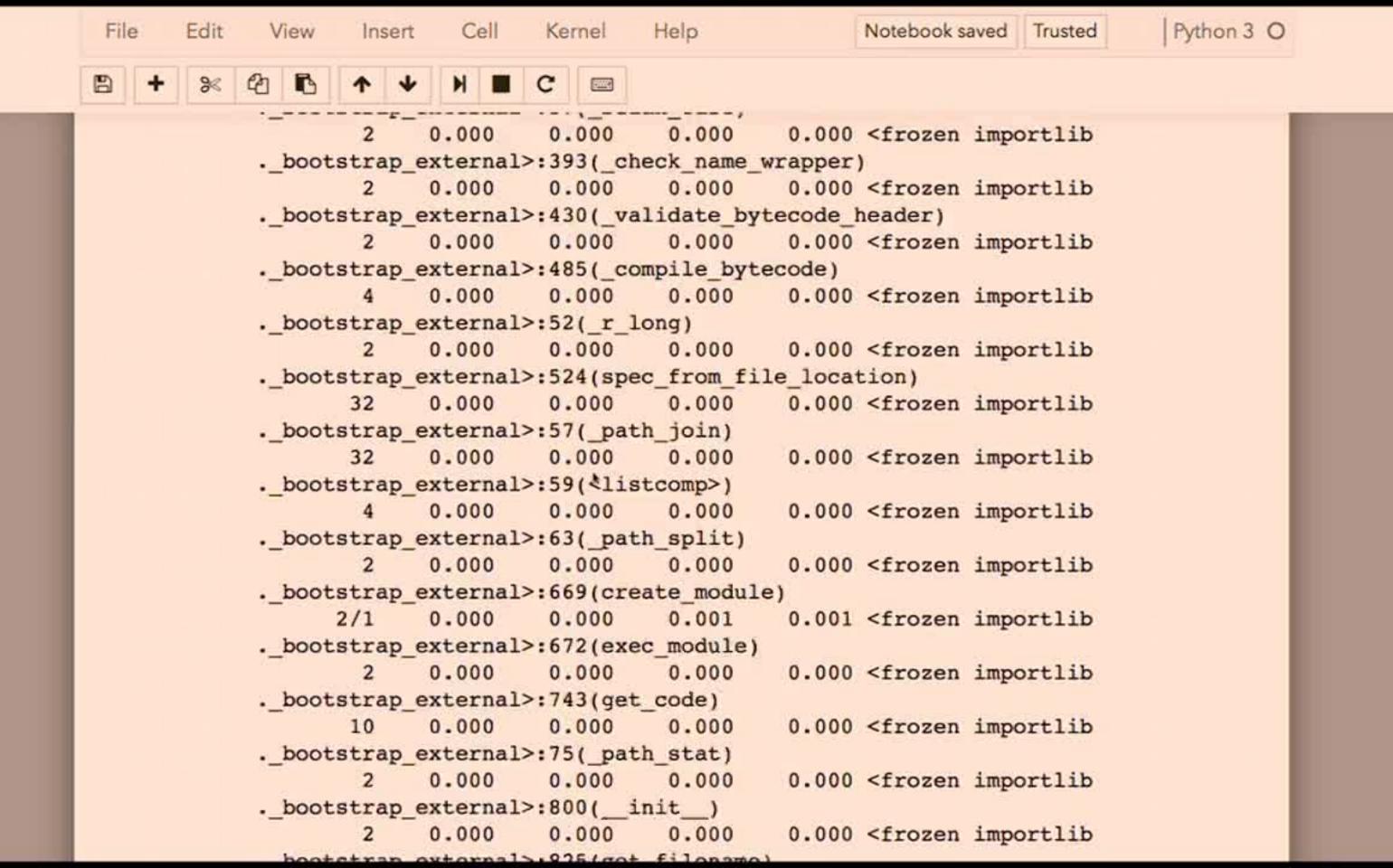


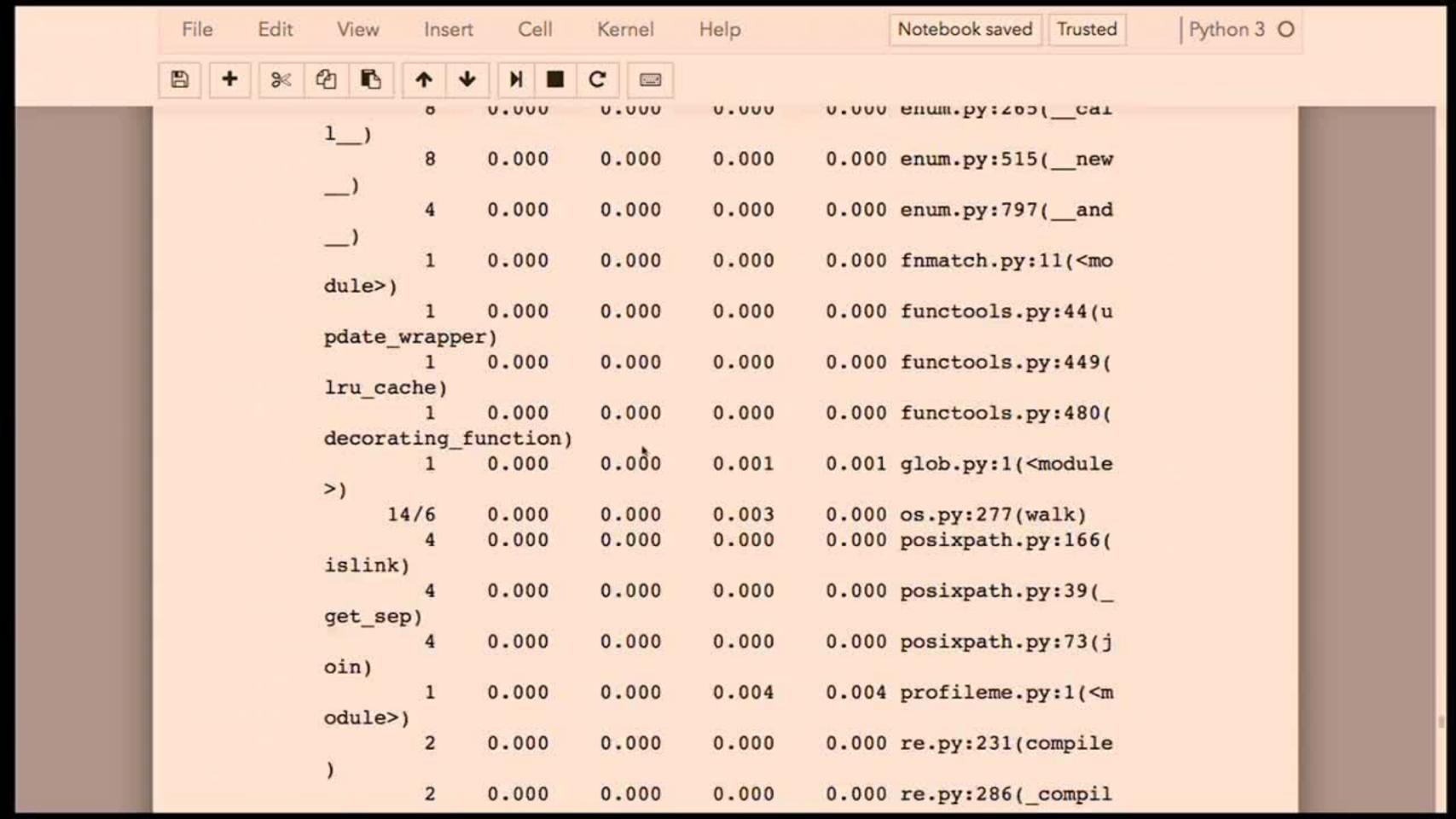


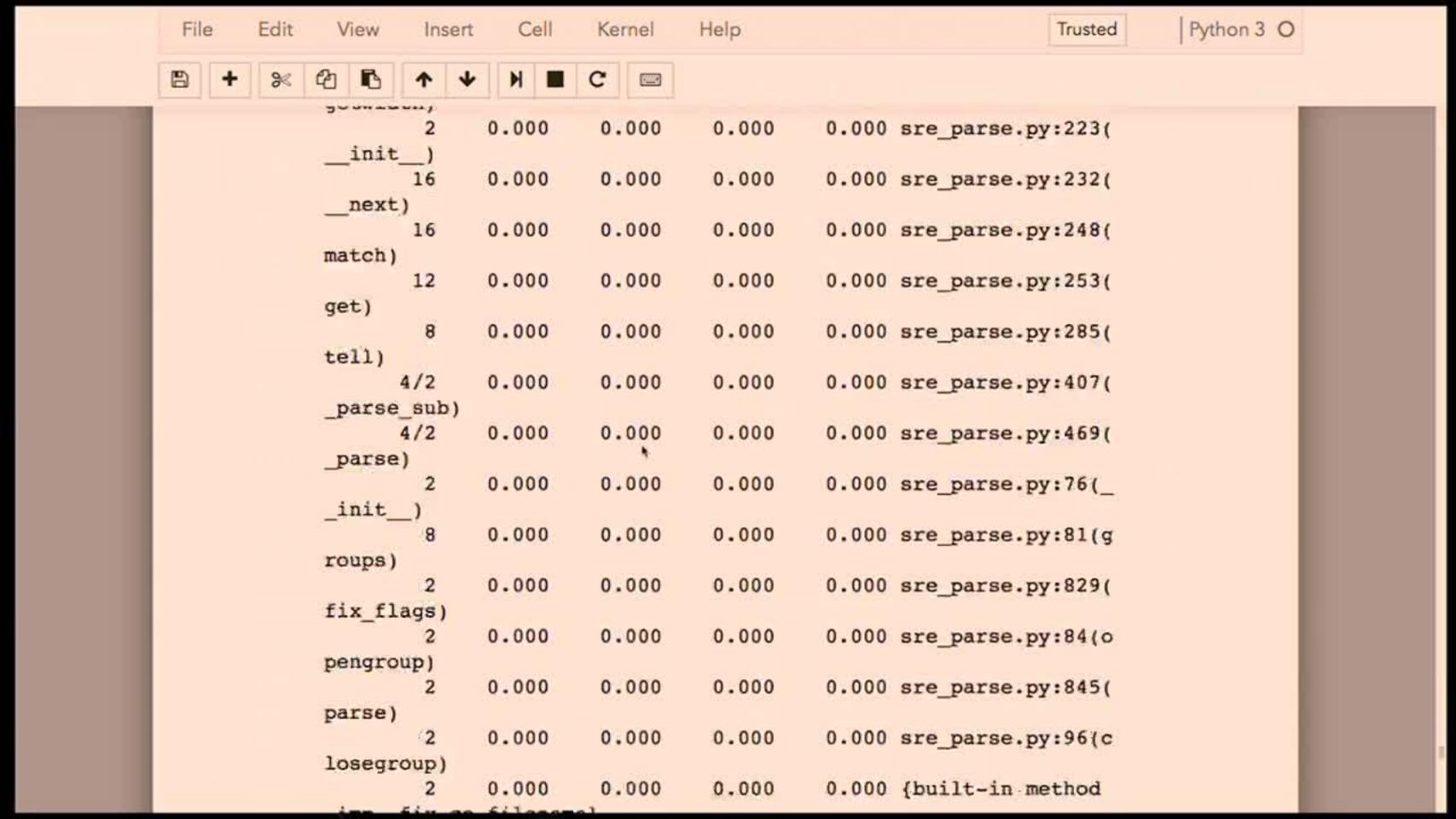


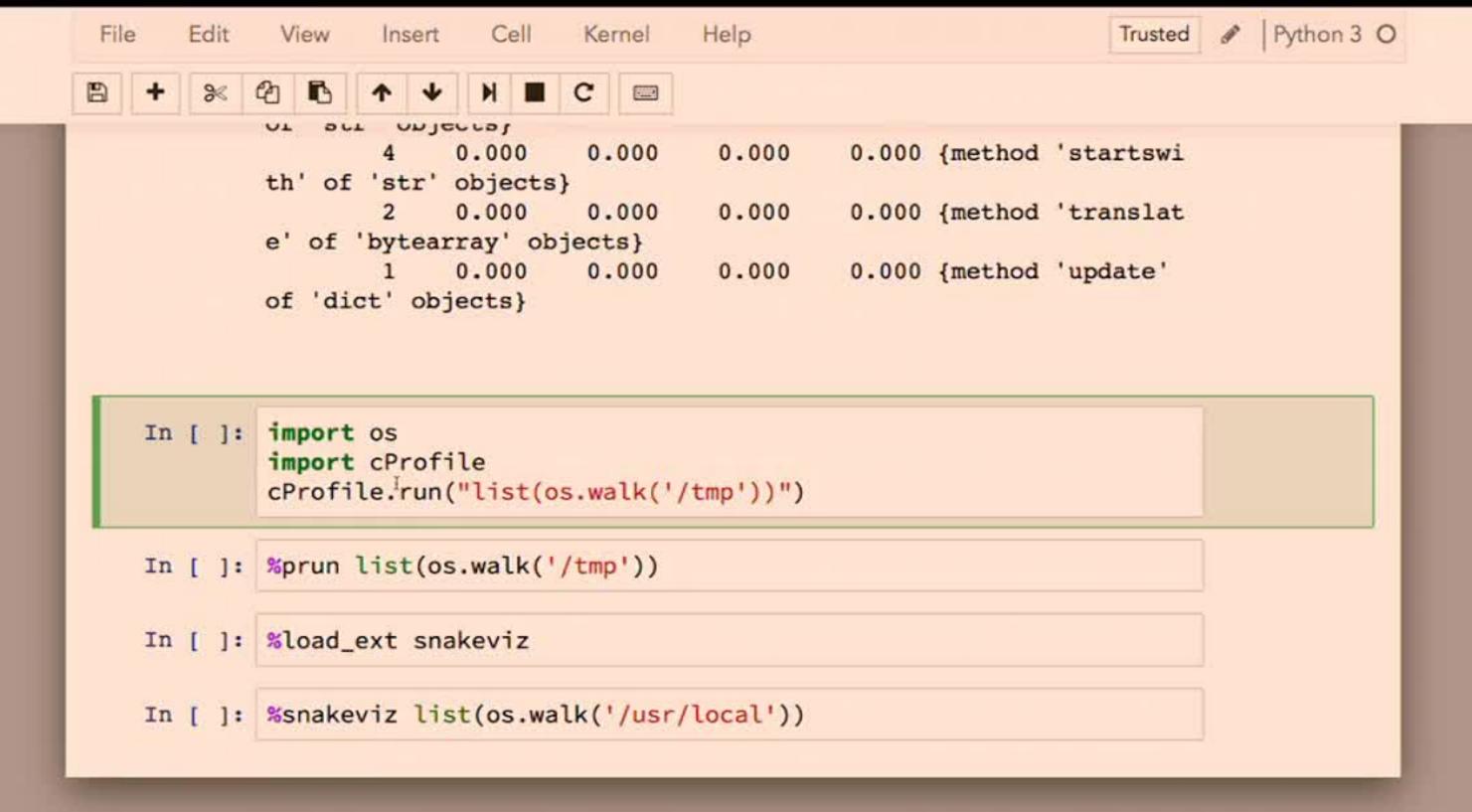


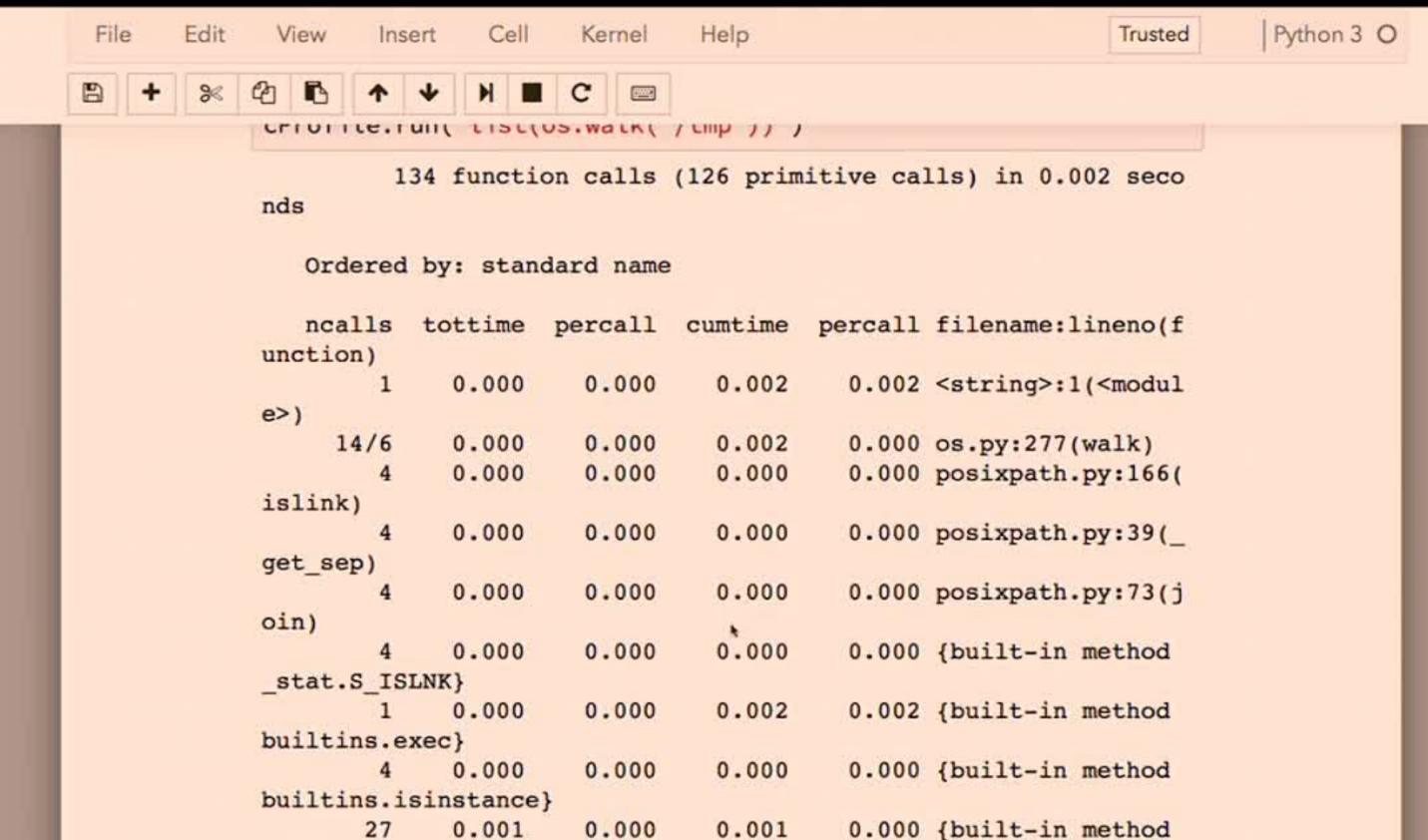












builtins.next}

posix.fspath}

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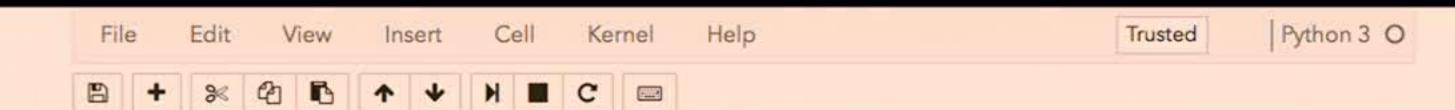
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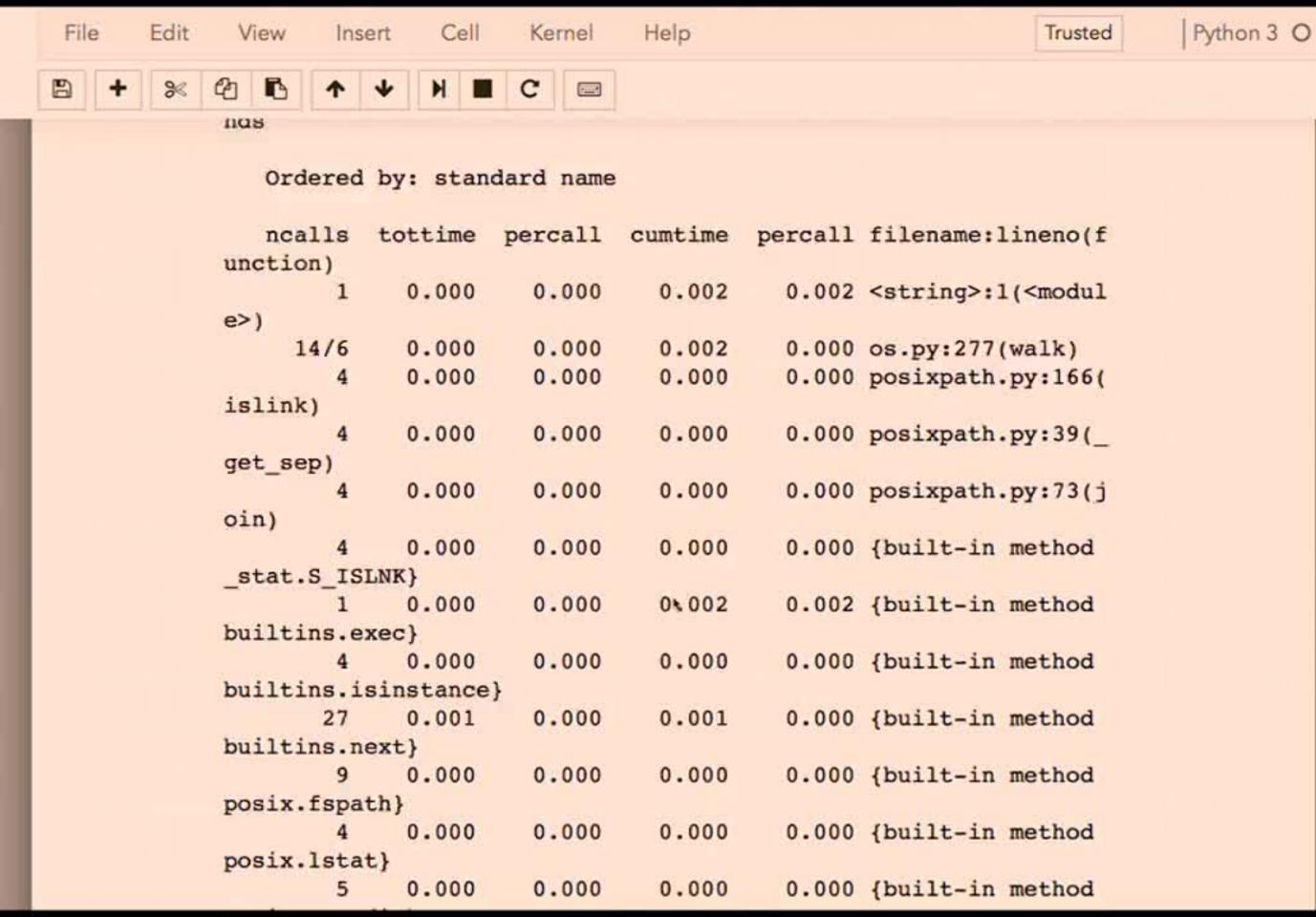
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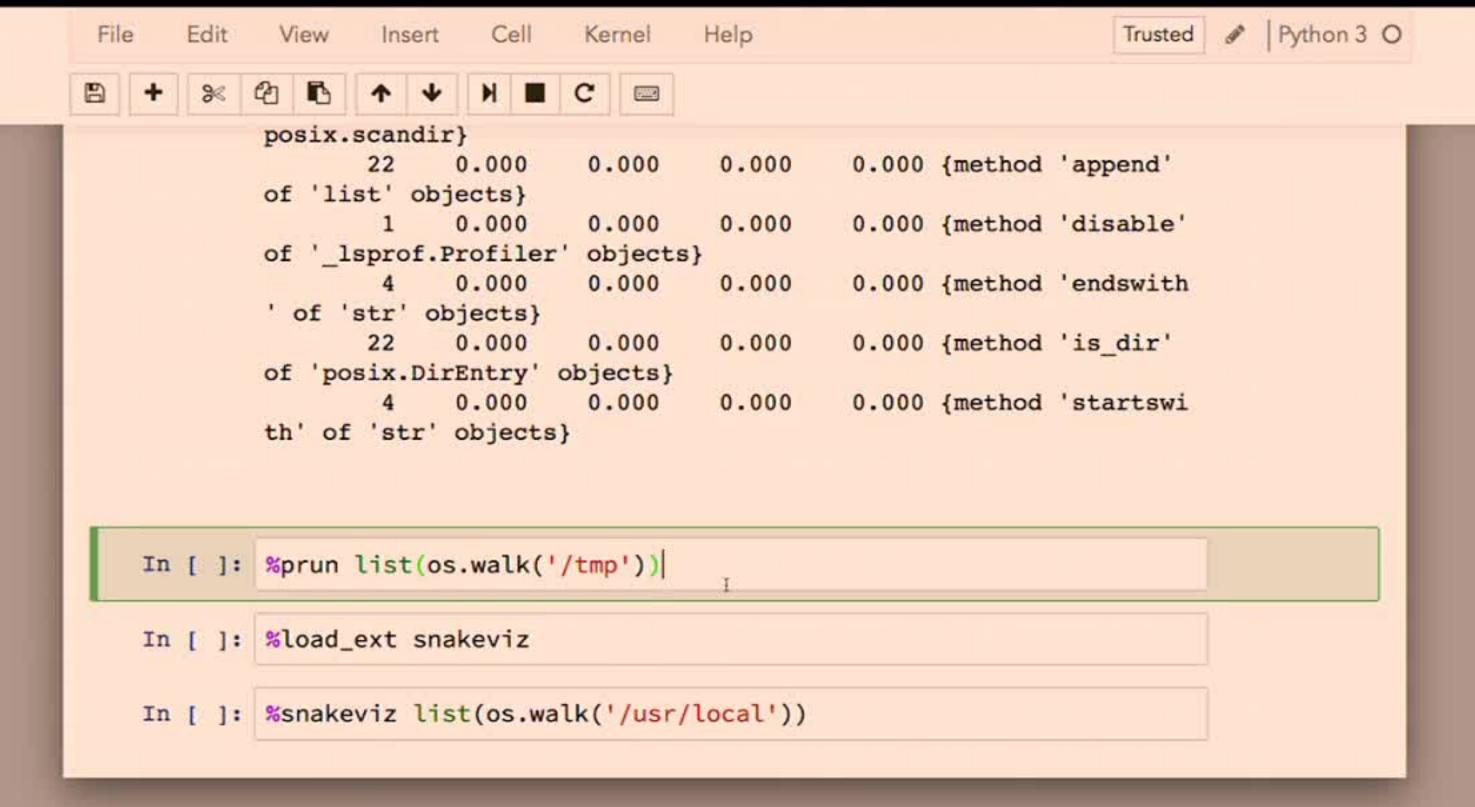


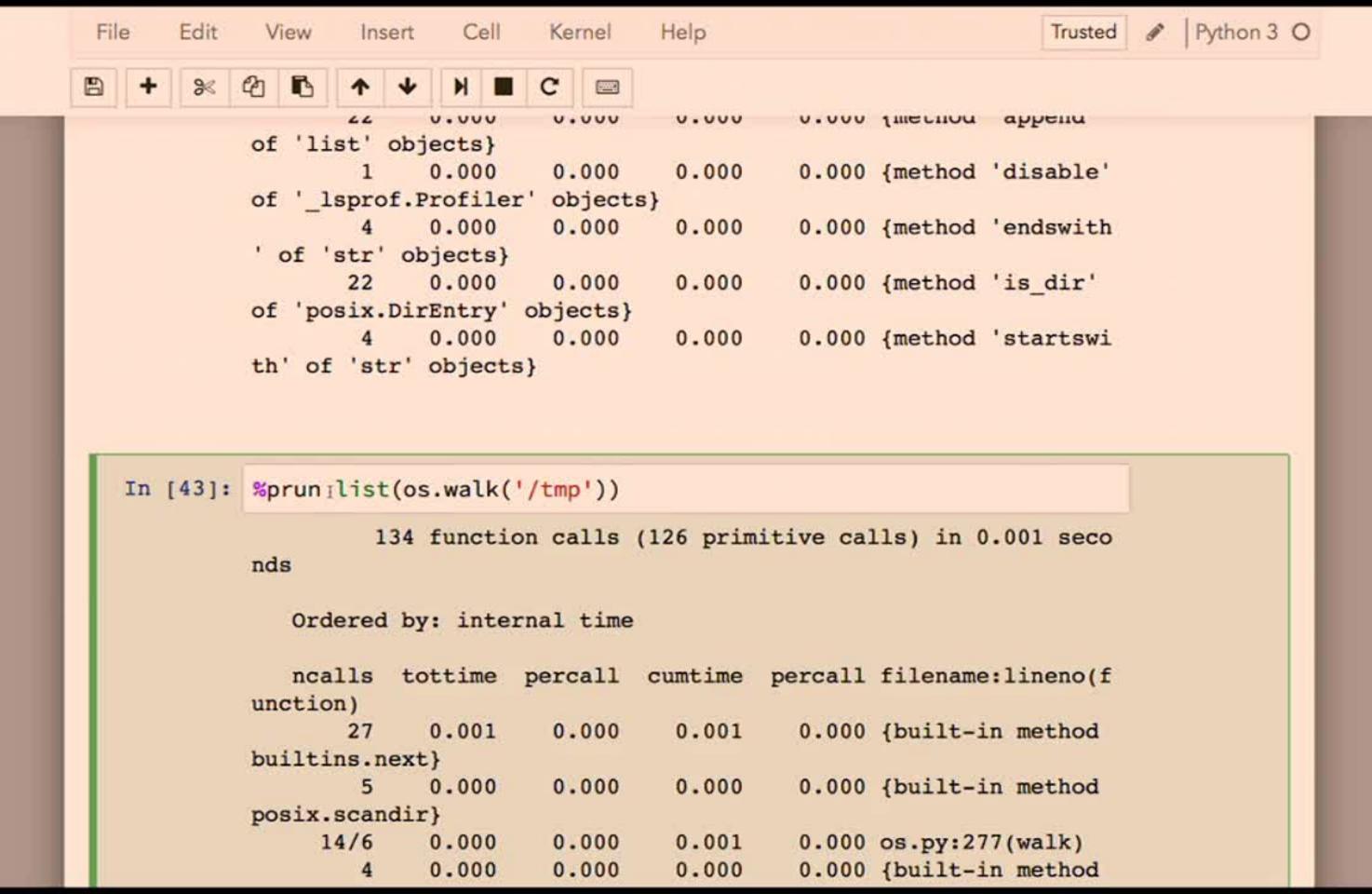
134 function calls (126 primitive calls) in 0.002 seconds

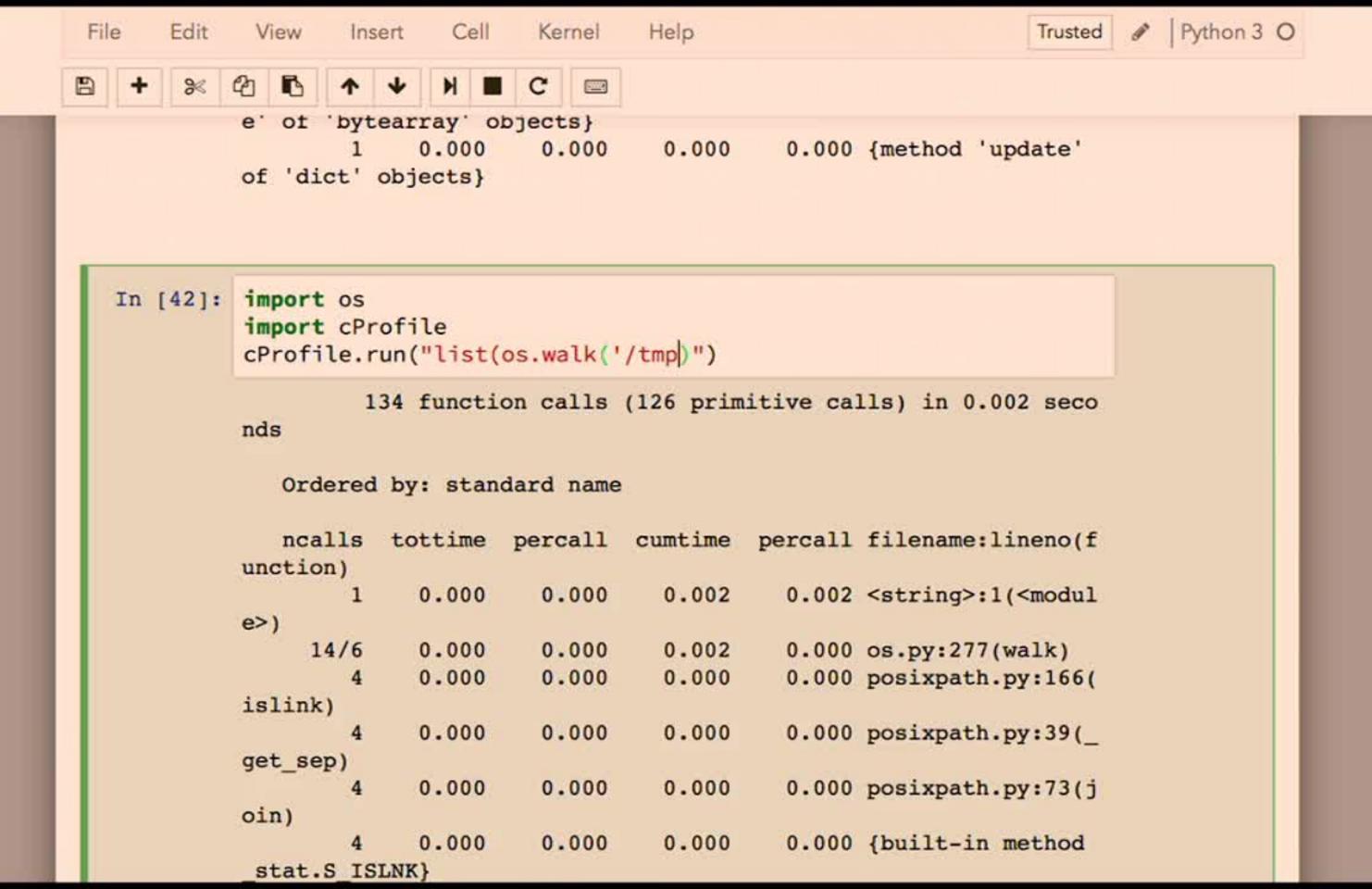
Ordered by: standard name

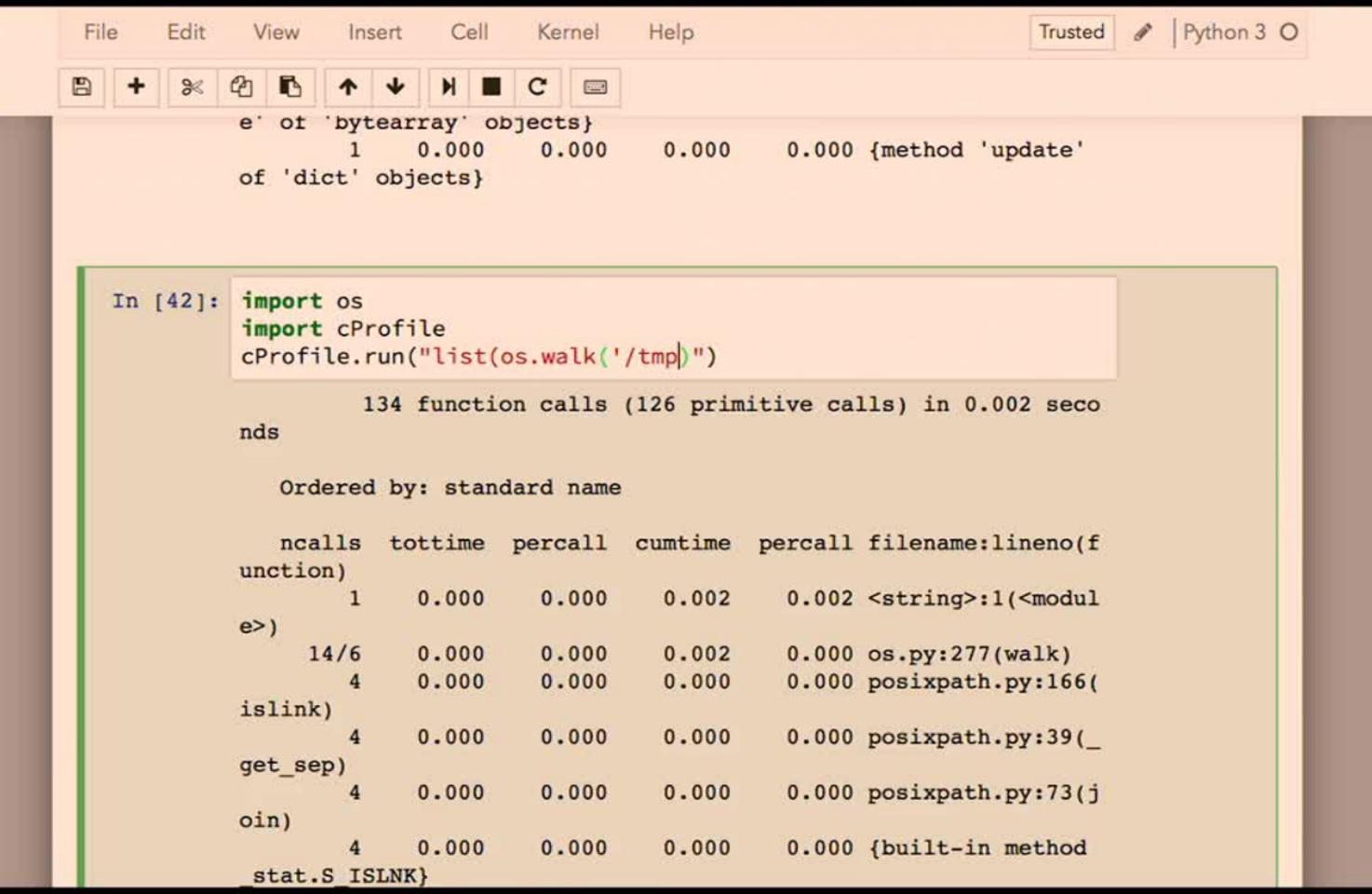
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unction)						
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e>)						
	14/6	0.000	0.000	0.002	0.000	os.py:277(walk)
	4	0.000	0.000	0.000	0.000	posixpath.py:166(
islink)						
	4	0.000	0.000	0.000	0.000	posixpath.py:39(_
get_sep)						
	4	0.000	0.000	0.000	0.000	posixpath.py:73(j
oin)						
	4	0.000	0.000	0.000	0.000	{built-in method
_stat.S_ISLNK}						
	1	0.000	0.000	0.002	0.002	{built-in method
builtins.exec}						
	4	0.000	0.000	0.000	0.000	{built-in method
builtins.isinstance}						
	27	0.001	0.000	0.001	0.000	{built-in method
builtins.next}						
	9	0.000	0.000	0.000	0.000	{built-in method
posix.fspath}						
	4	0.000	0.000	0.000	0.000	{built-in method

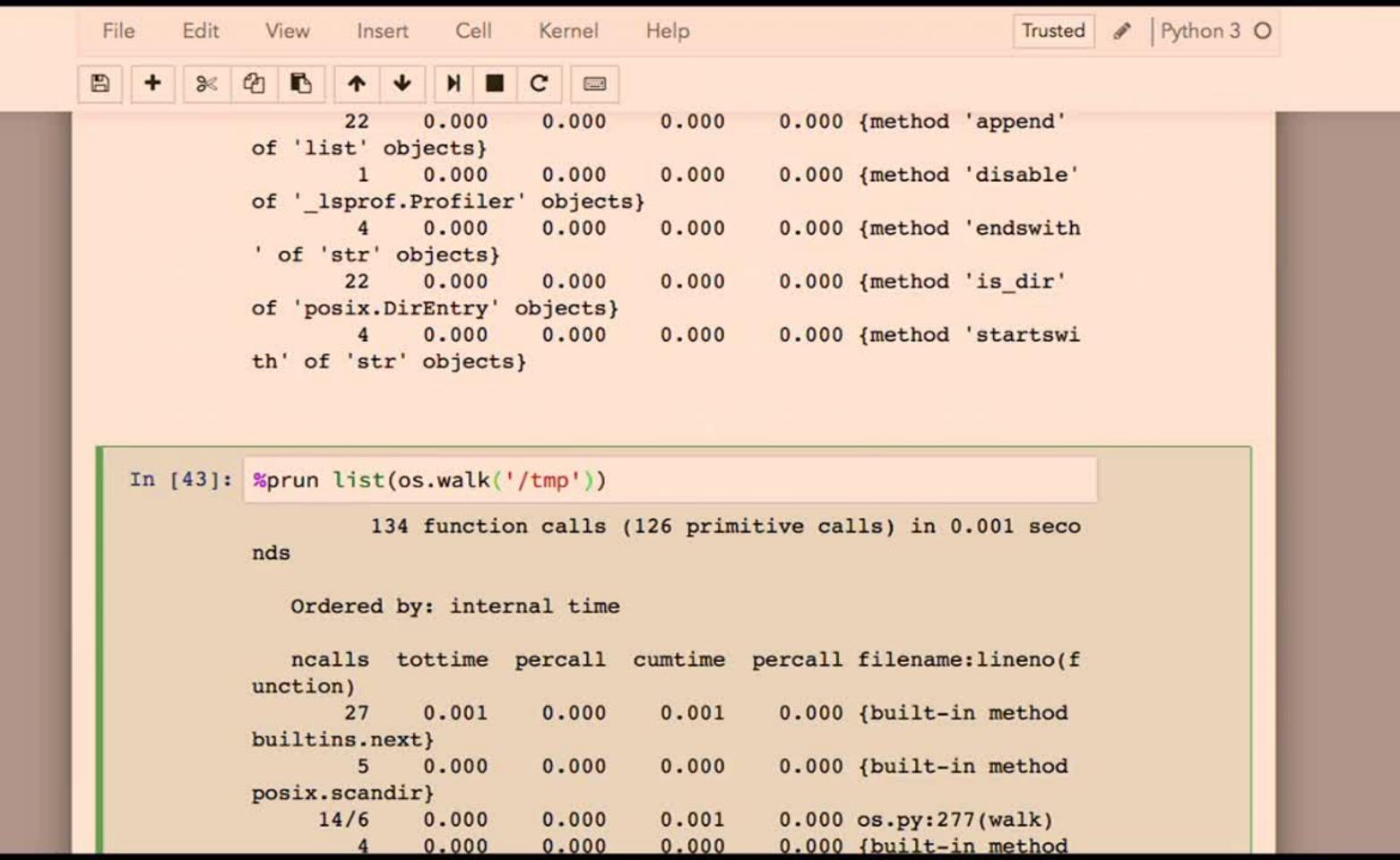


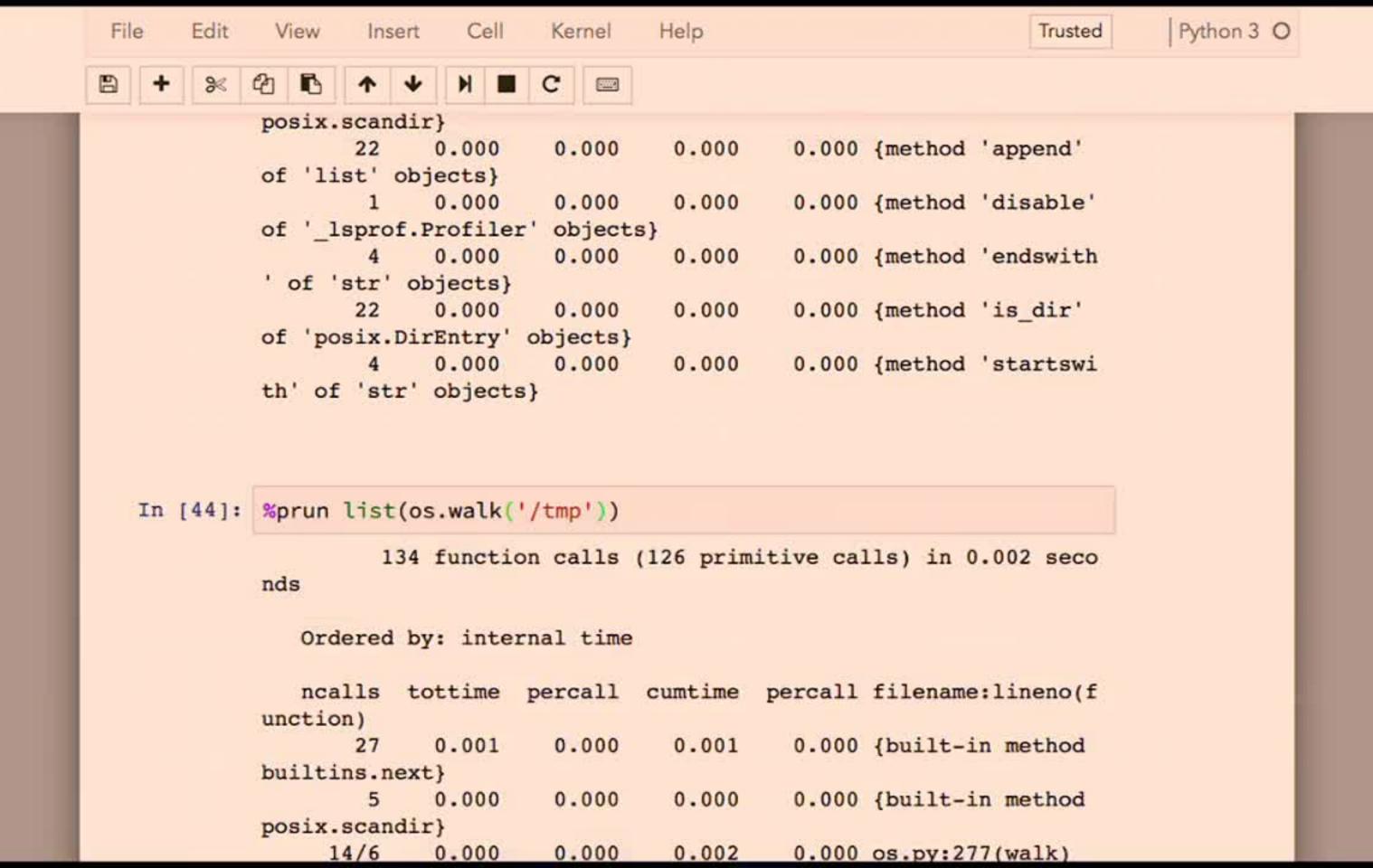


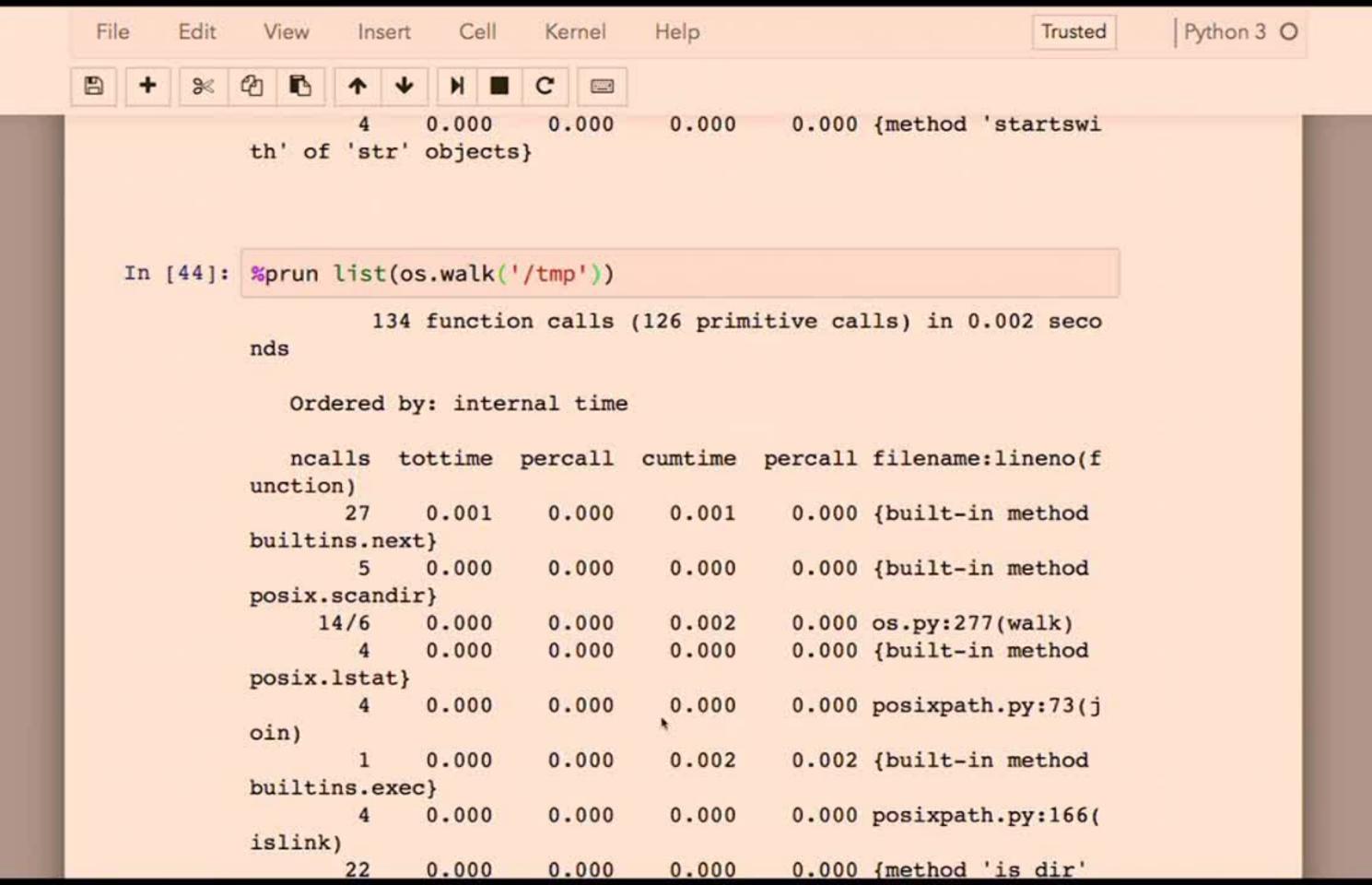


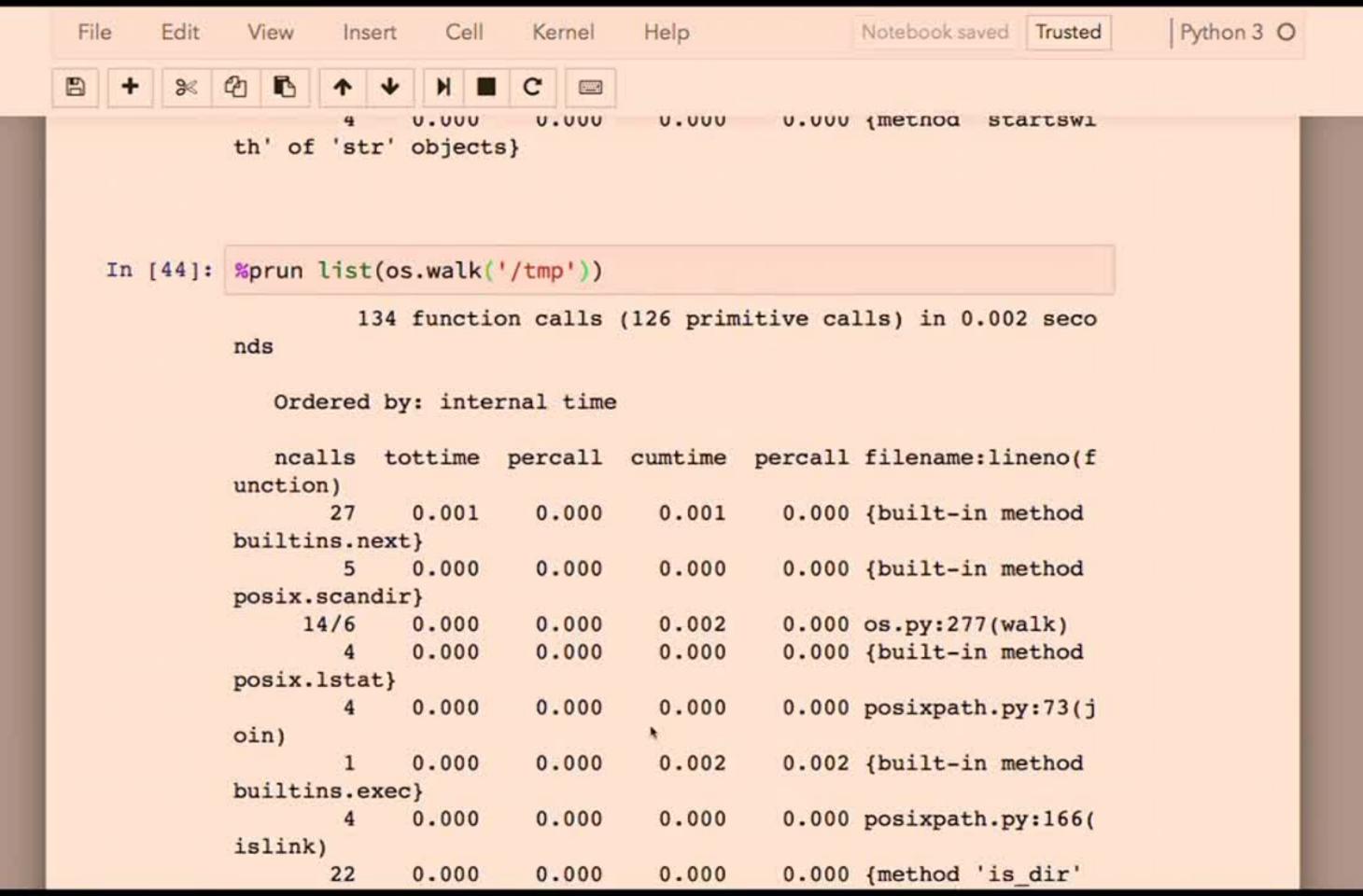


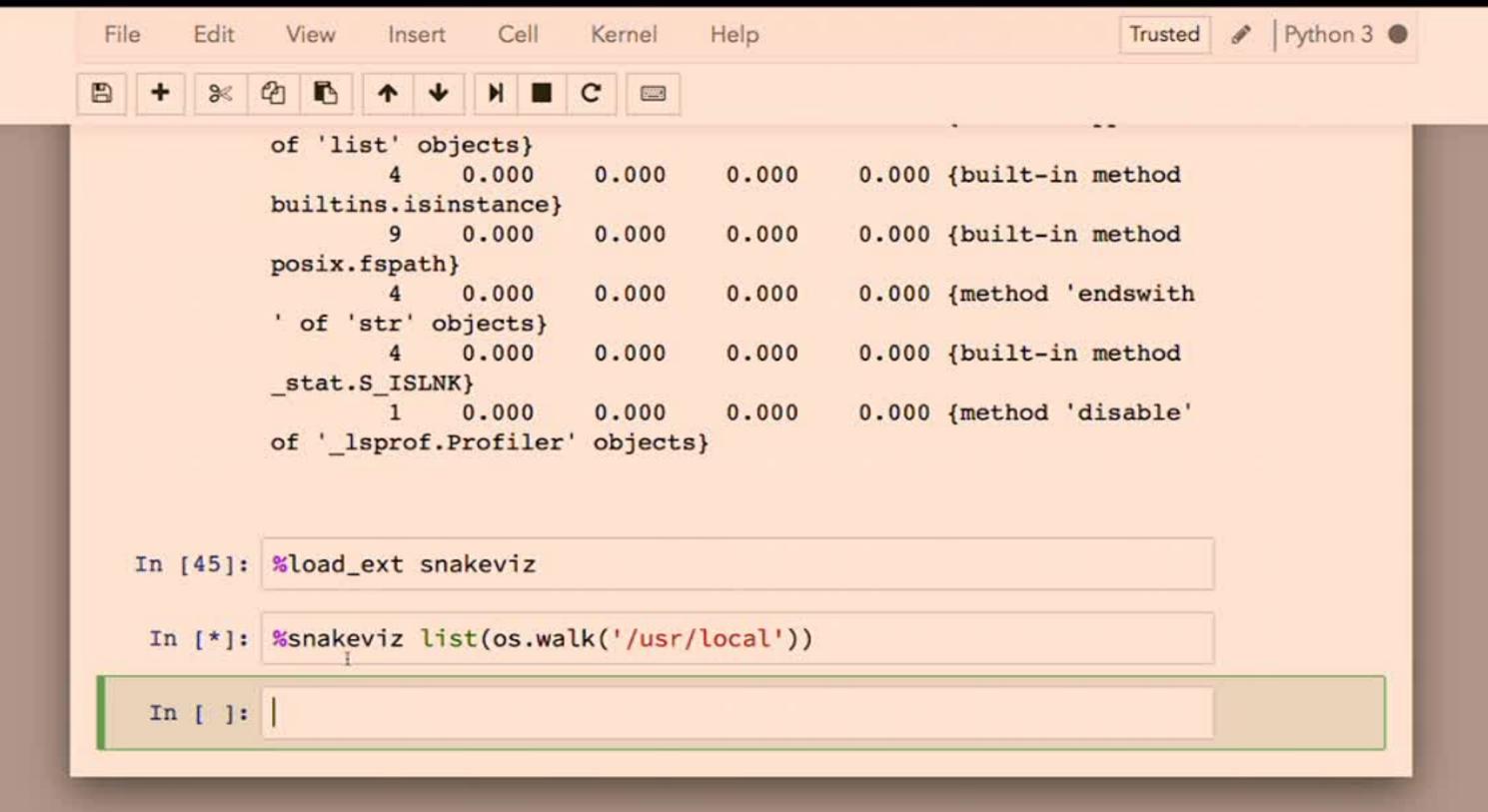




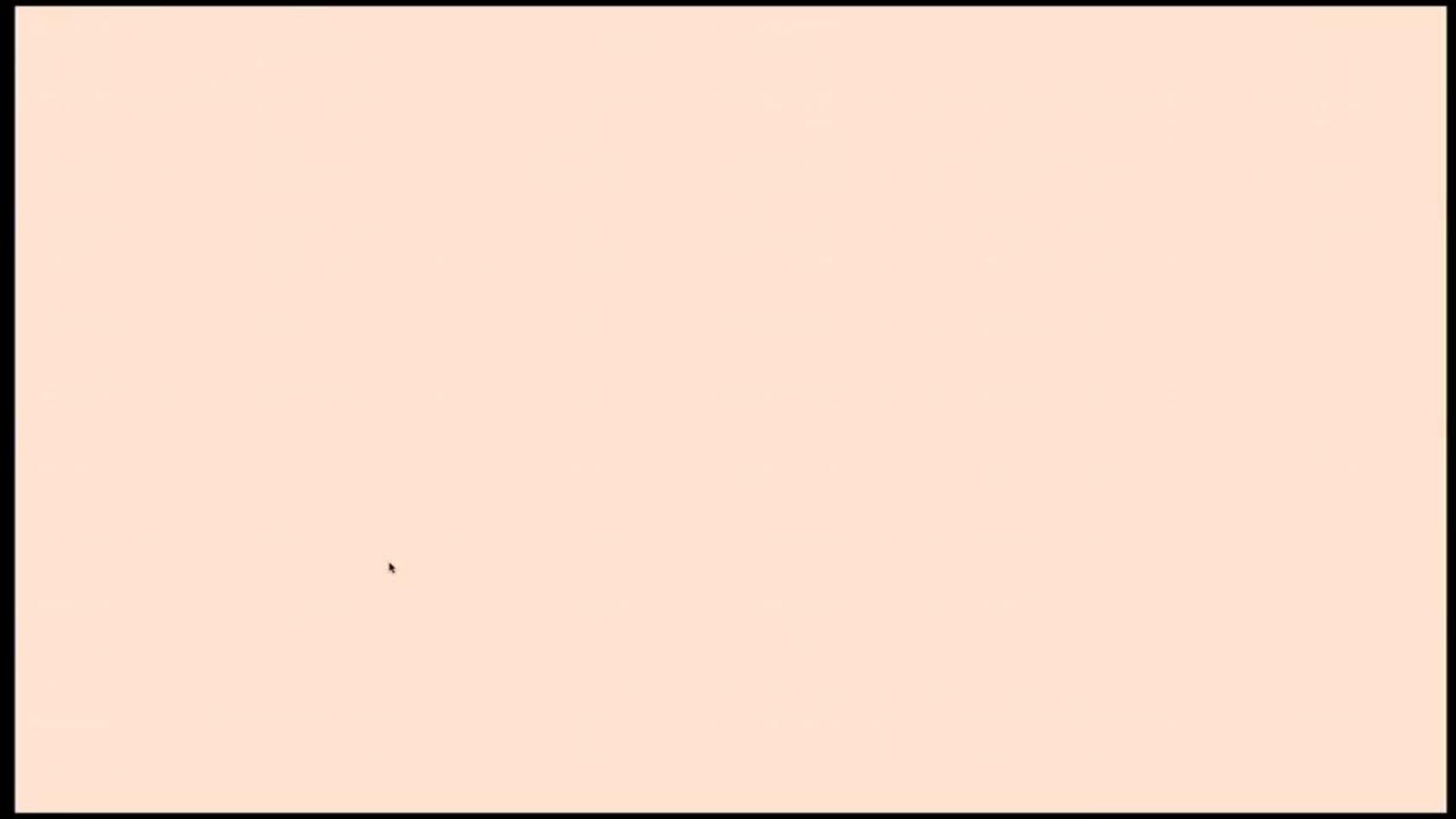


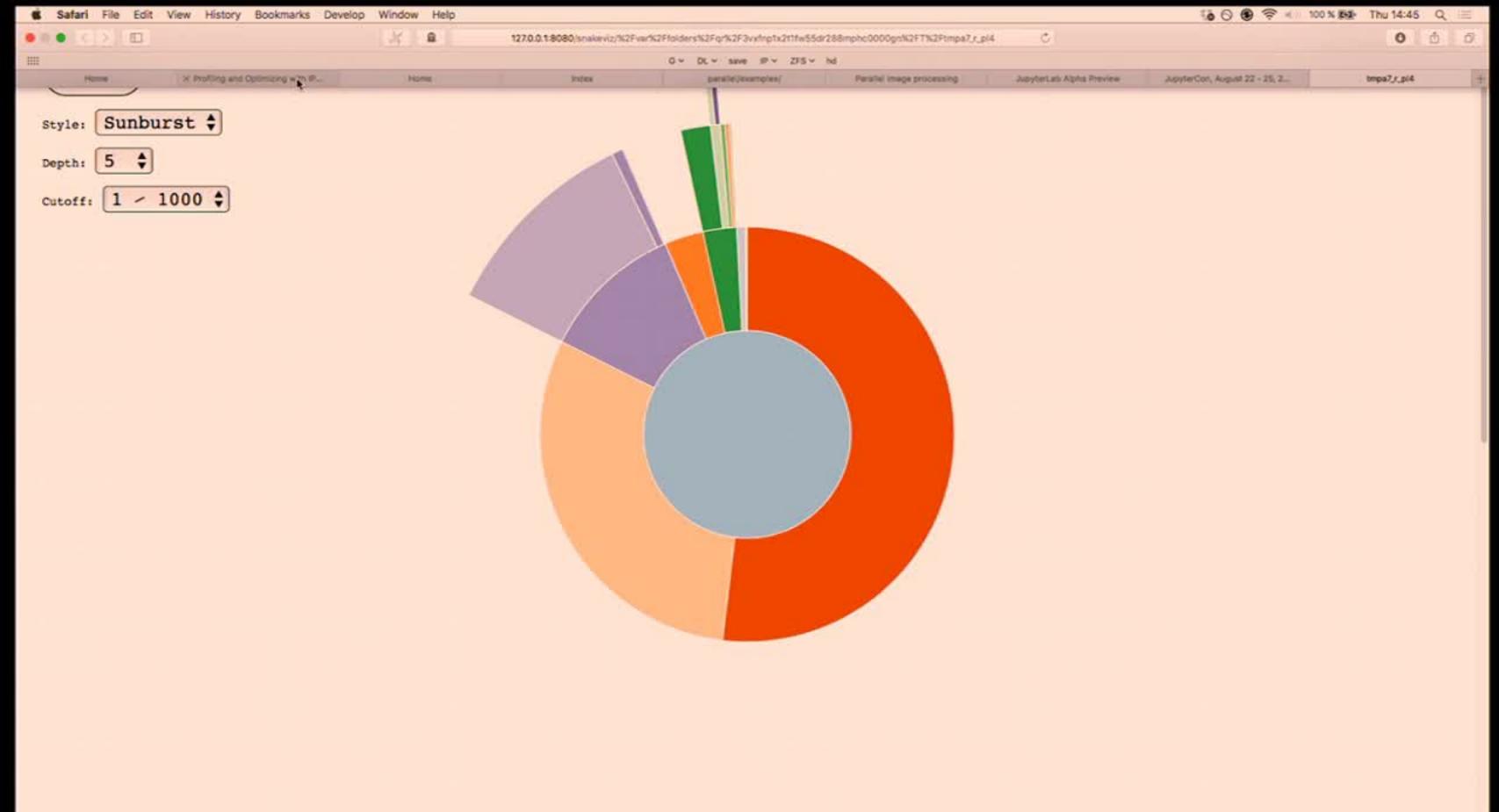


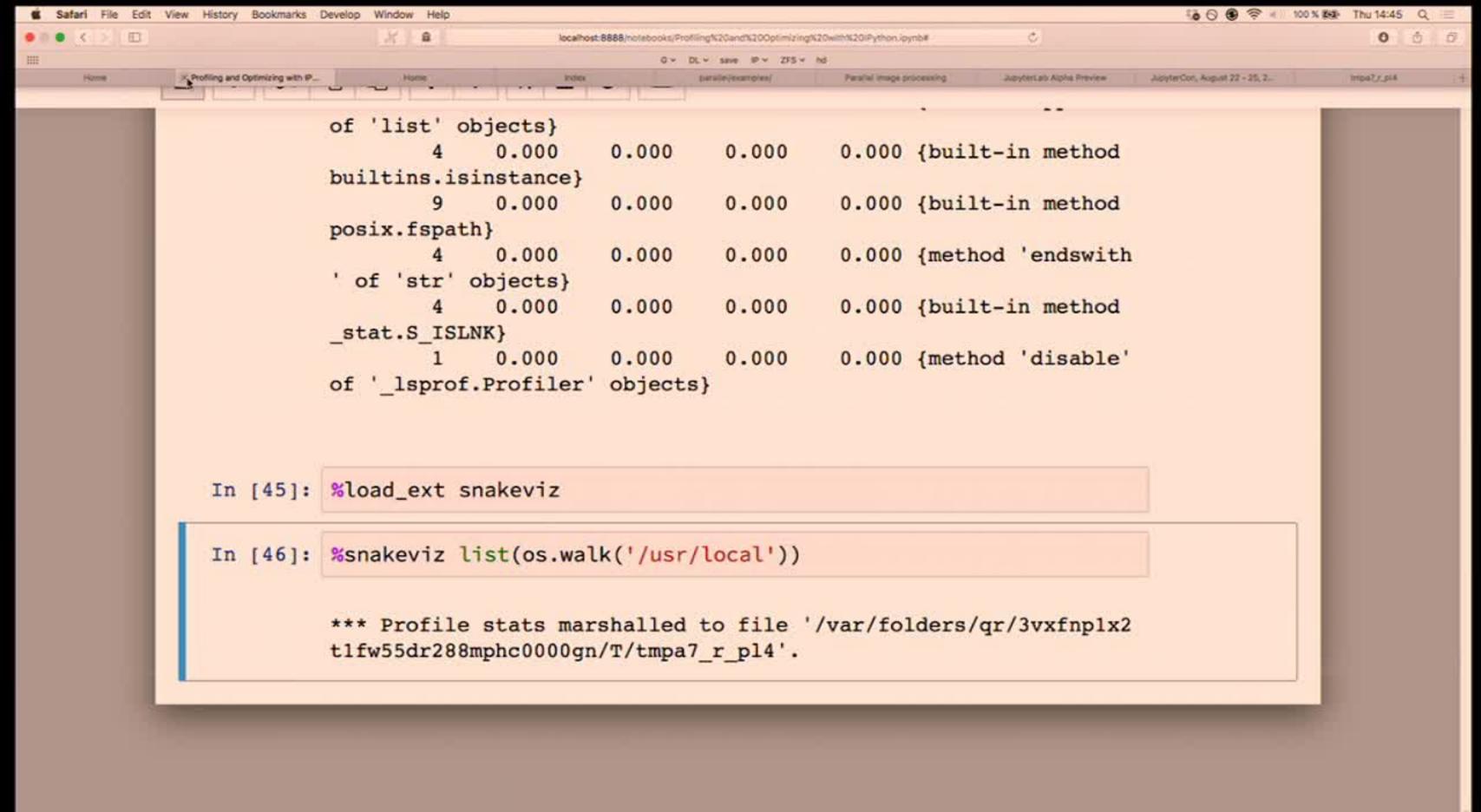


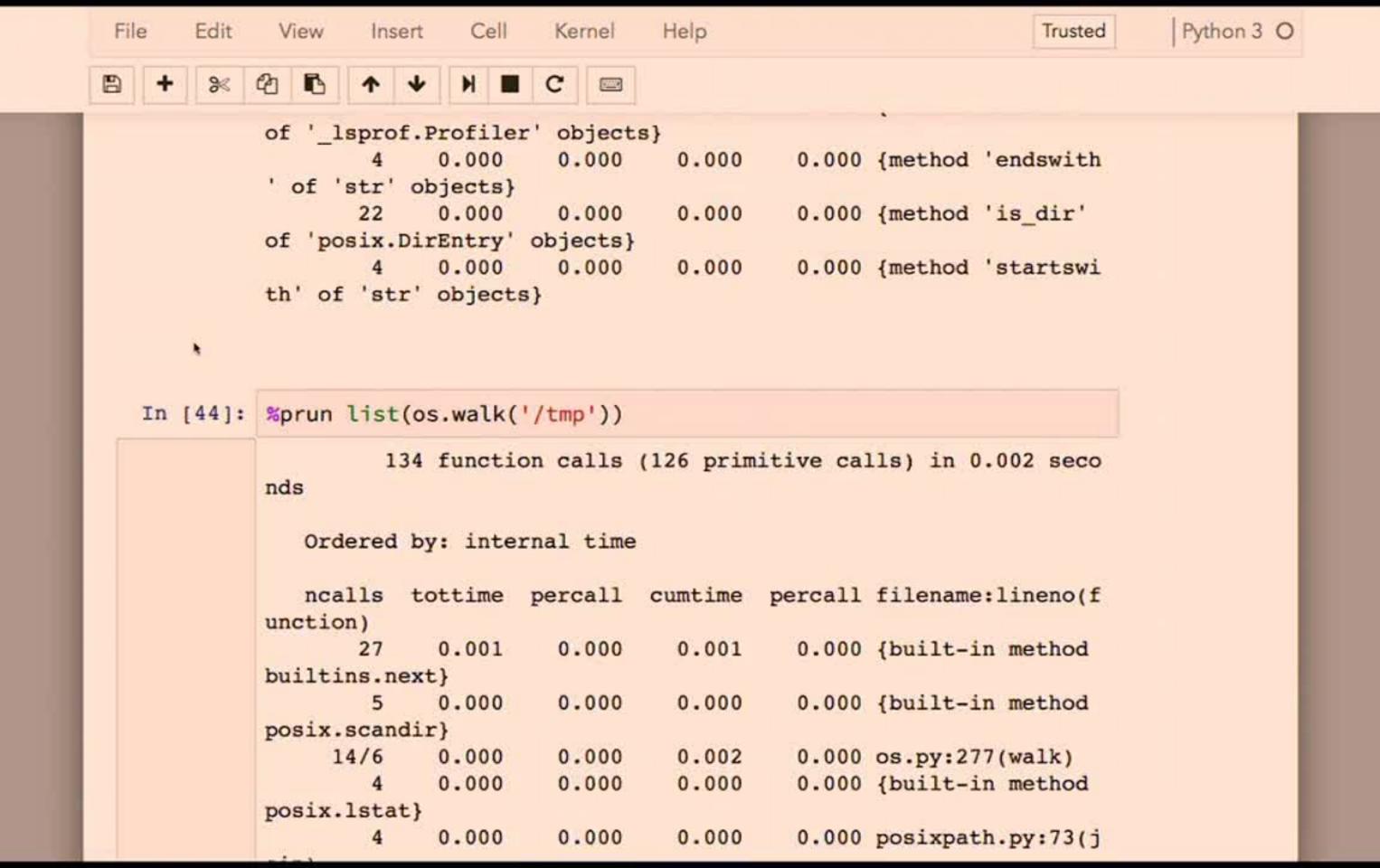


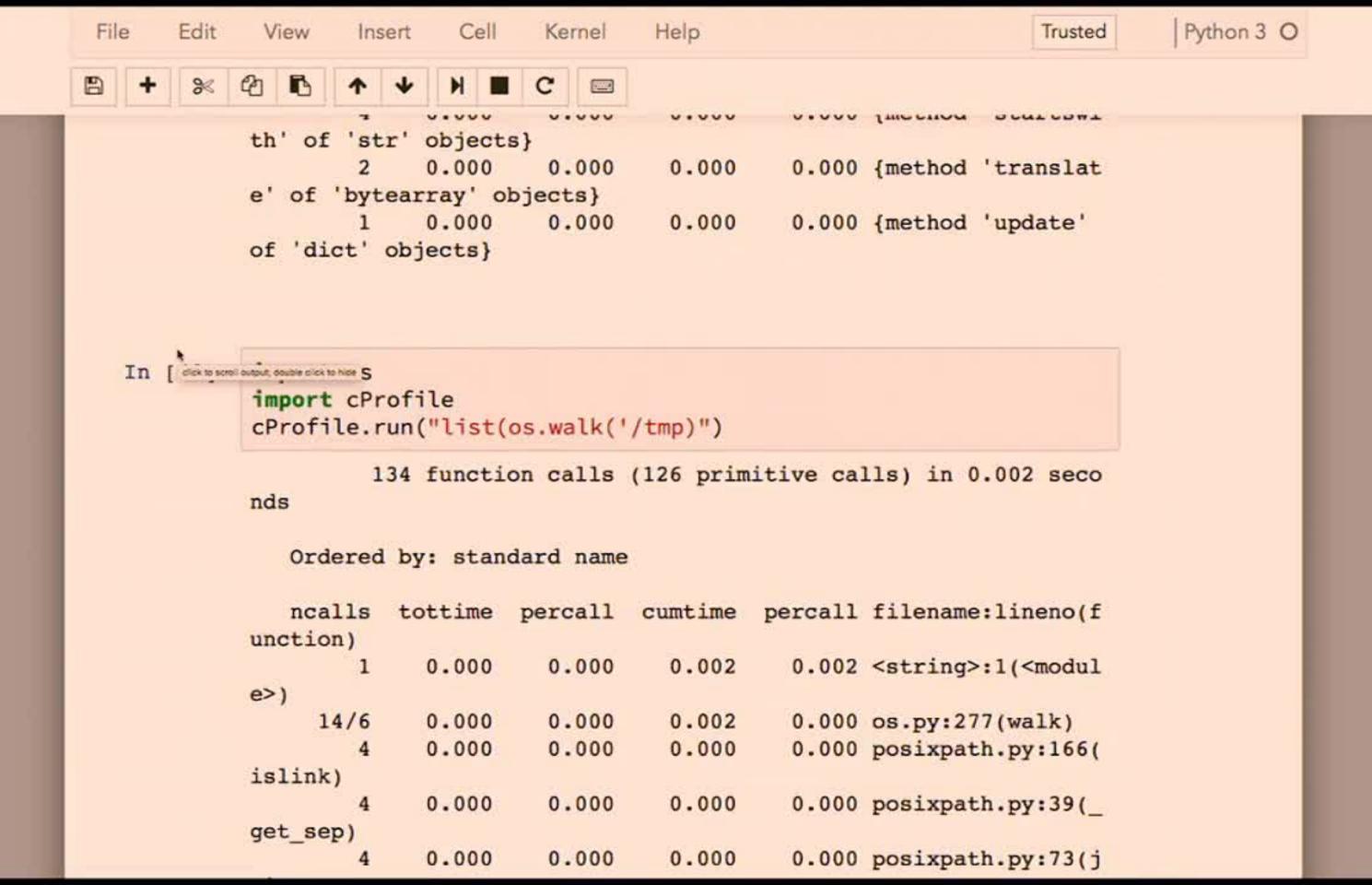
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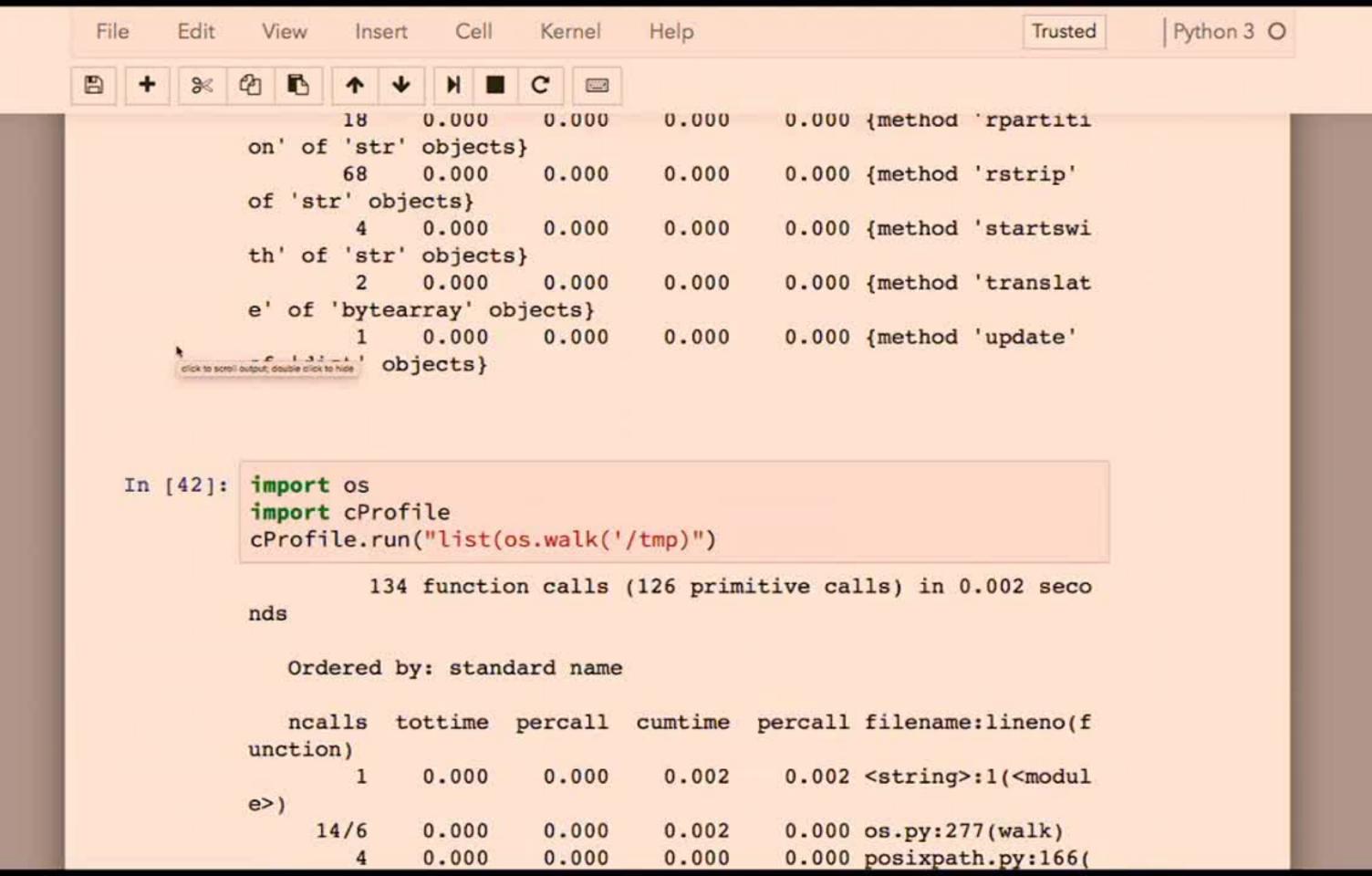


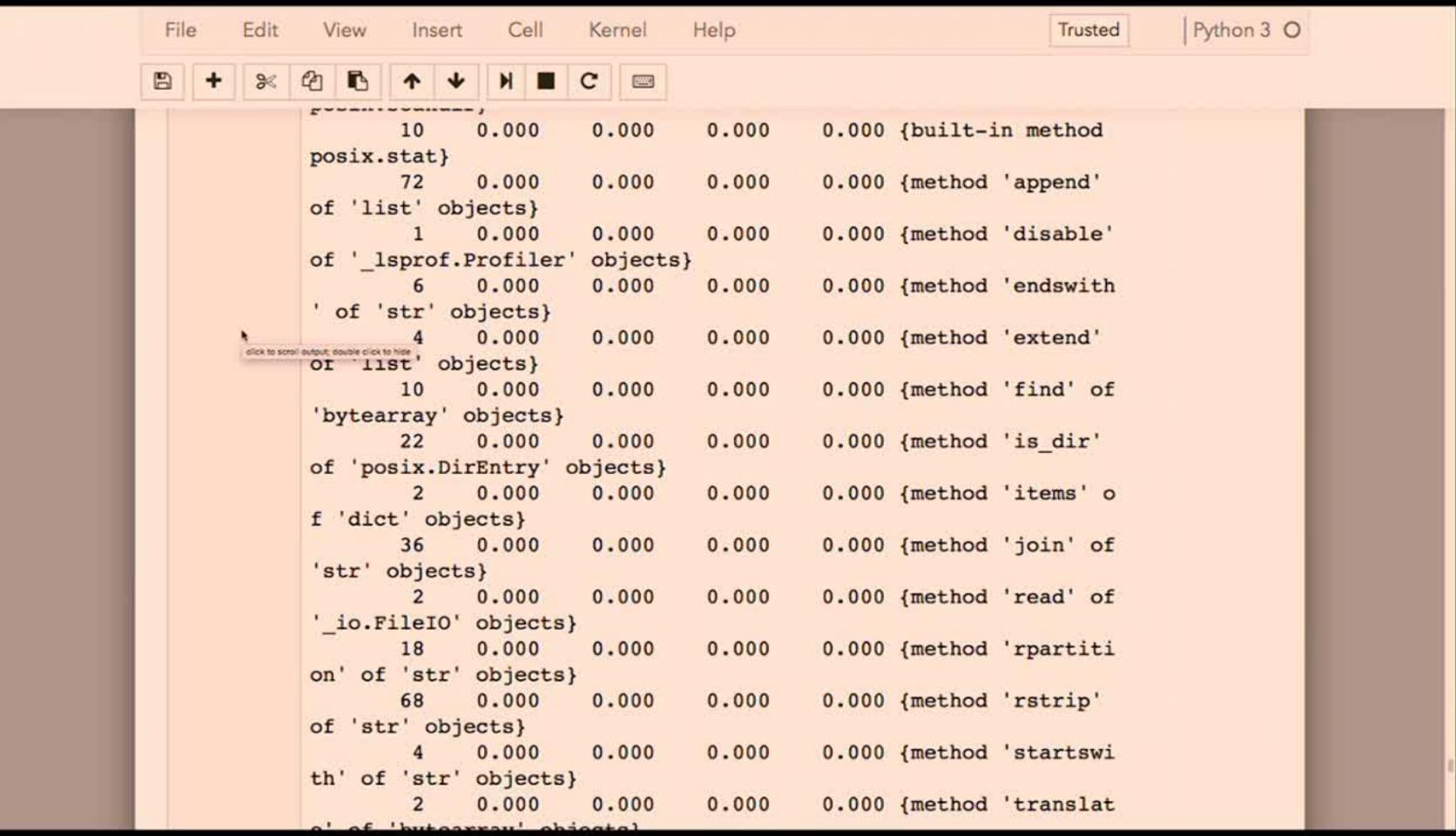


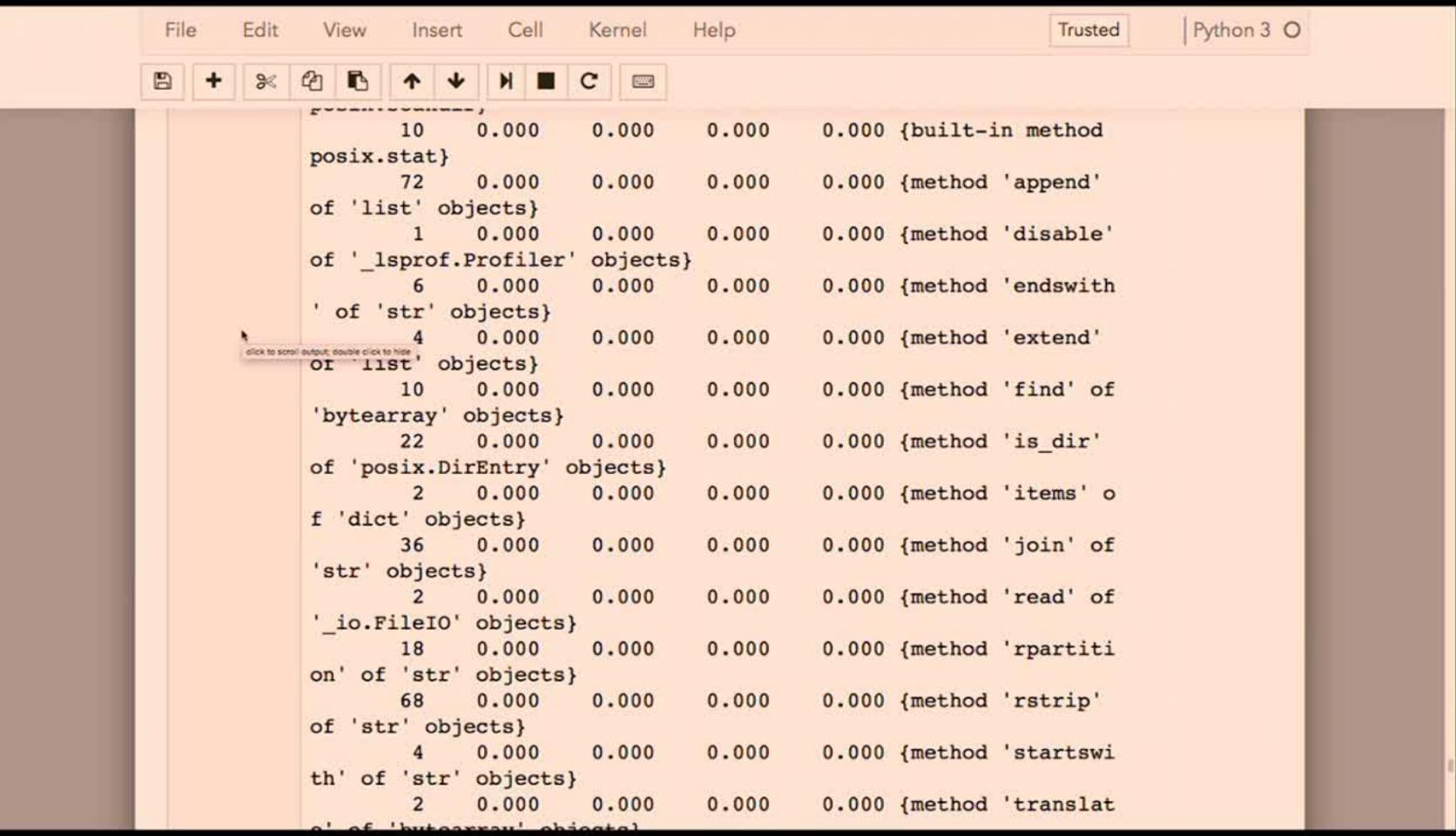


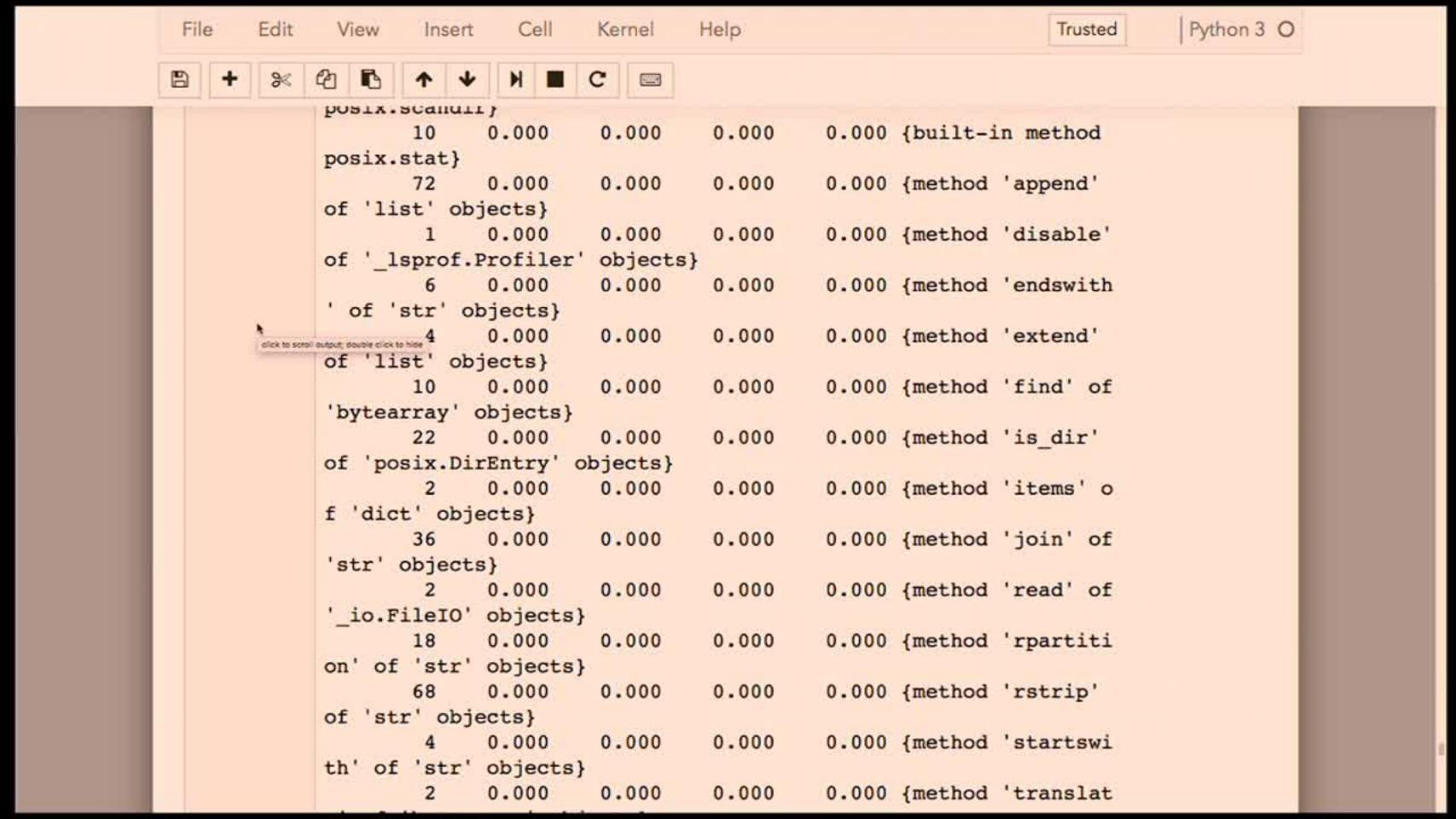


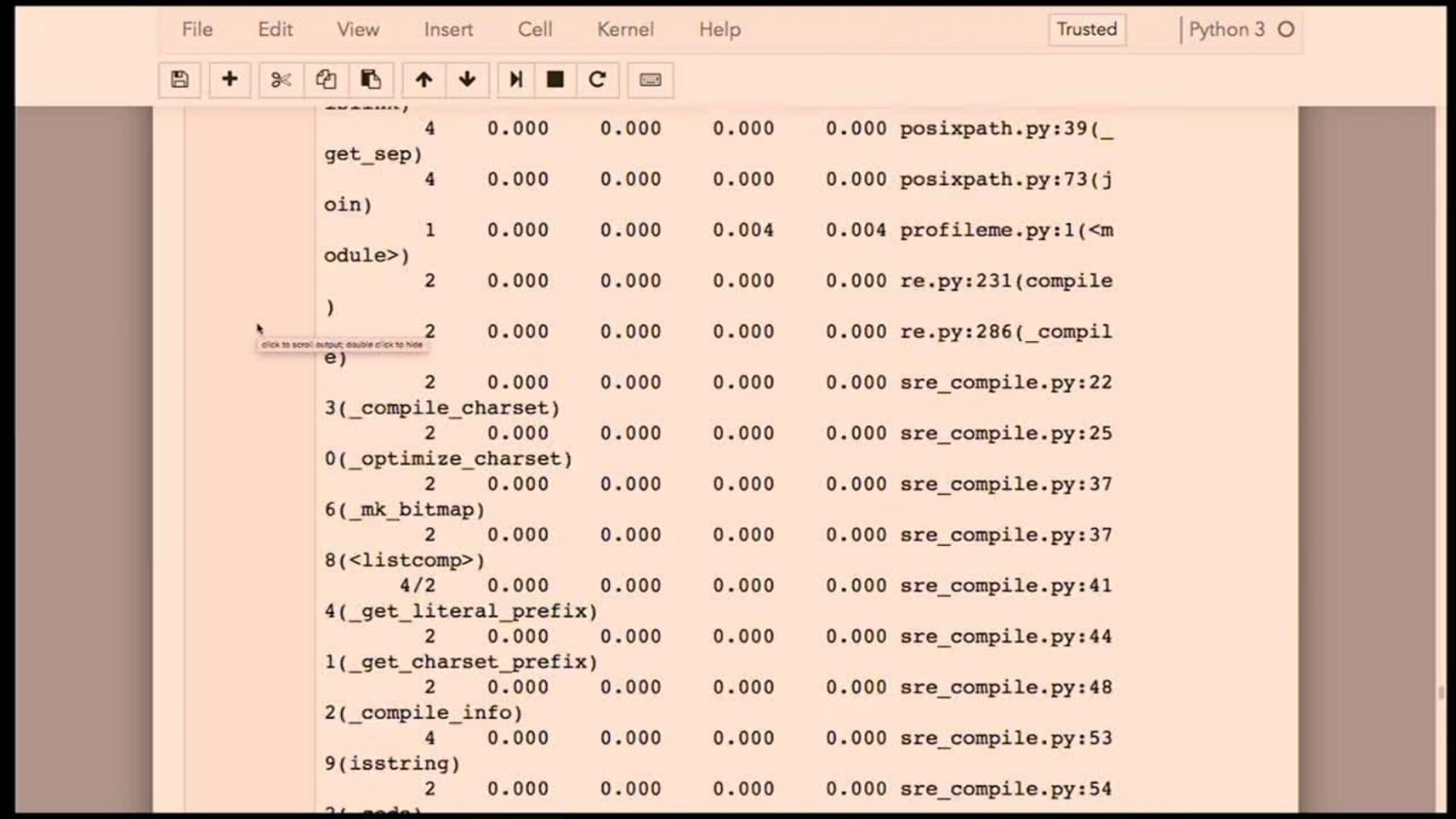


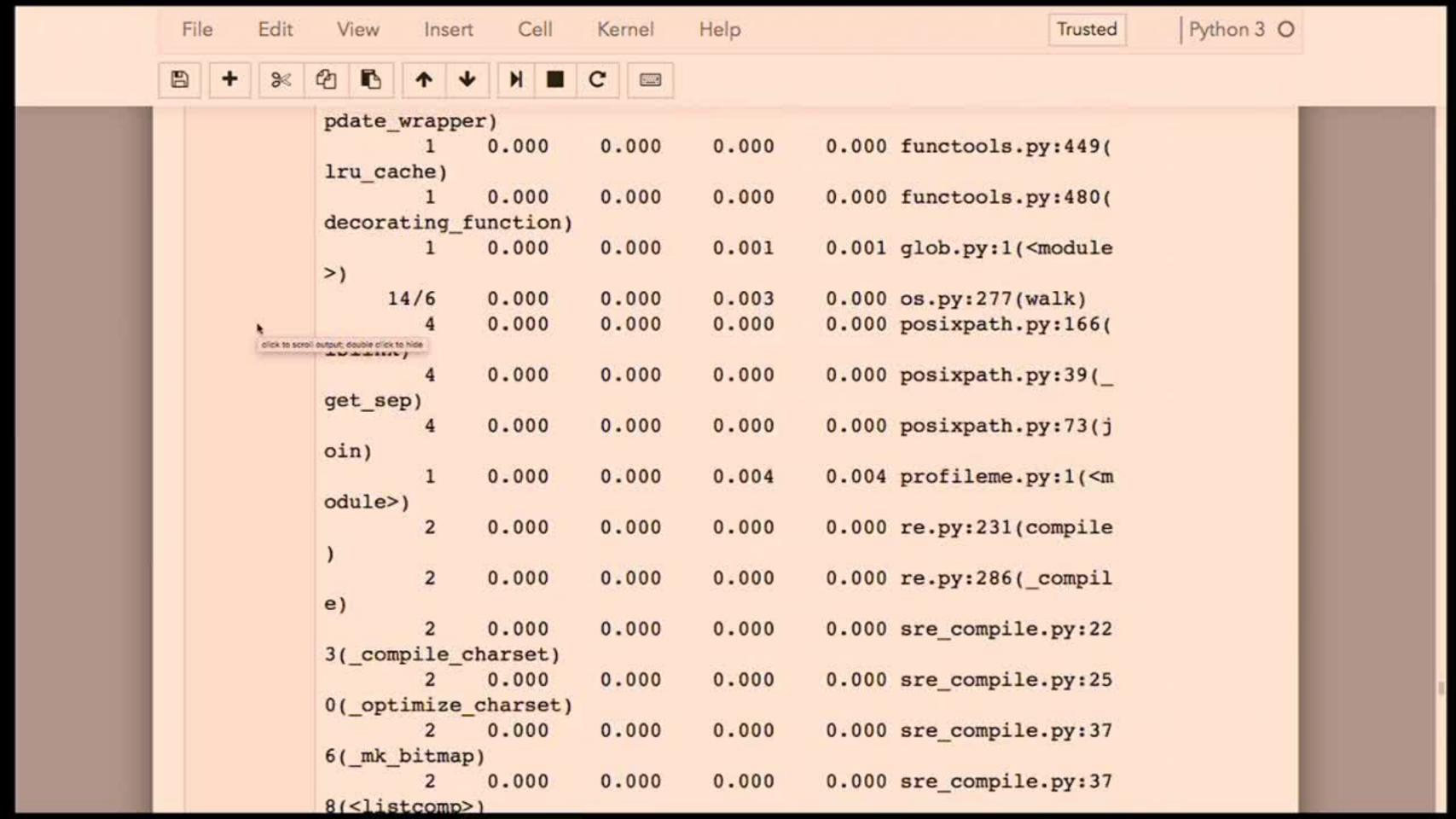


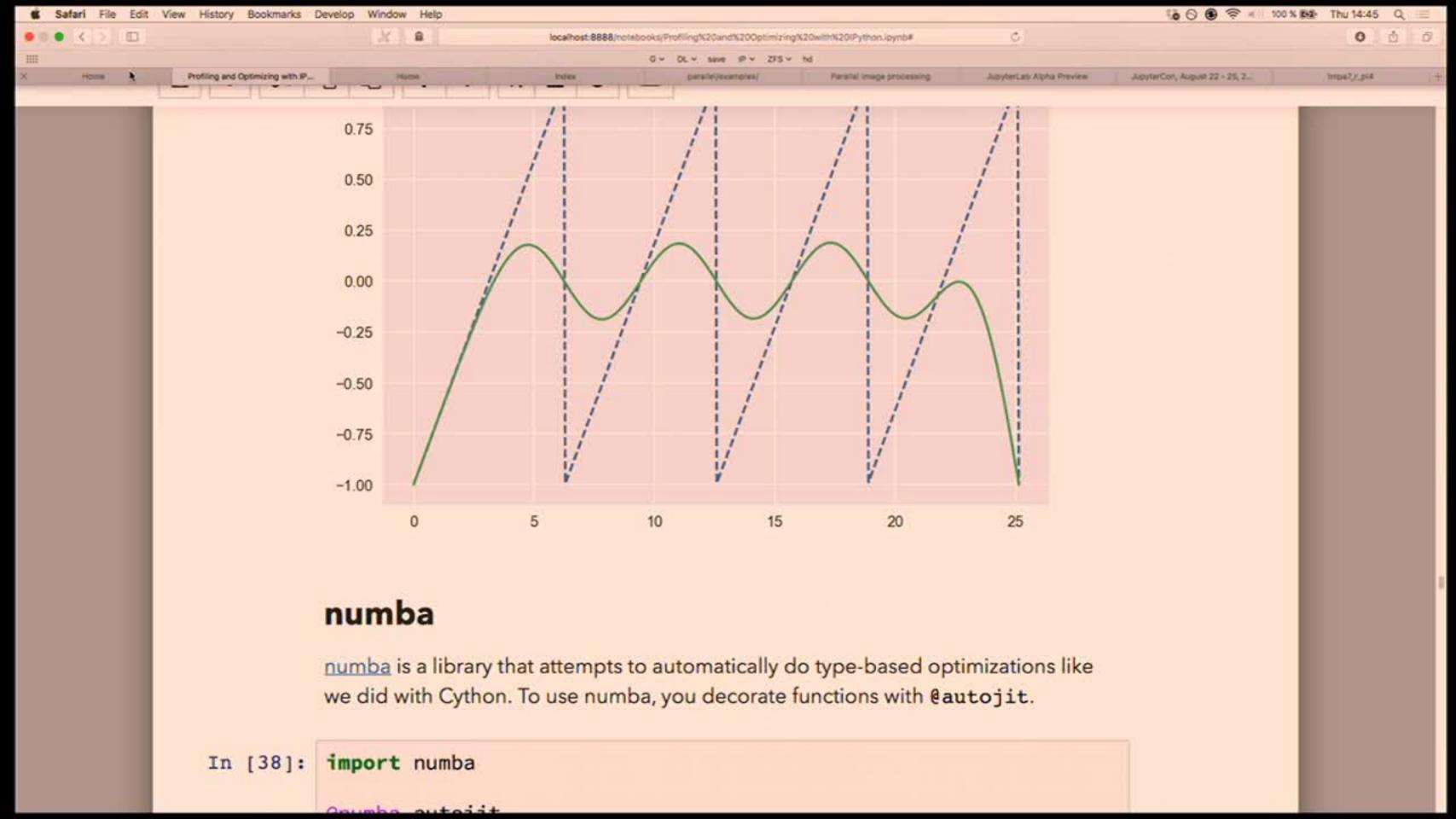


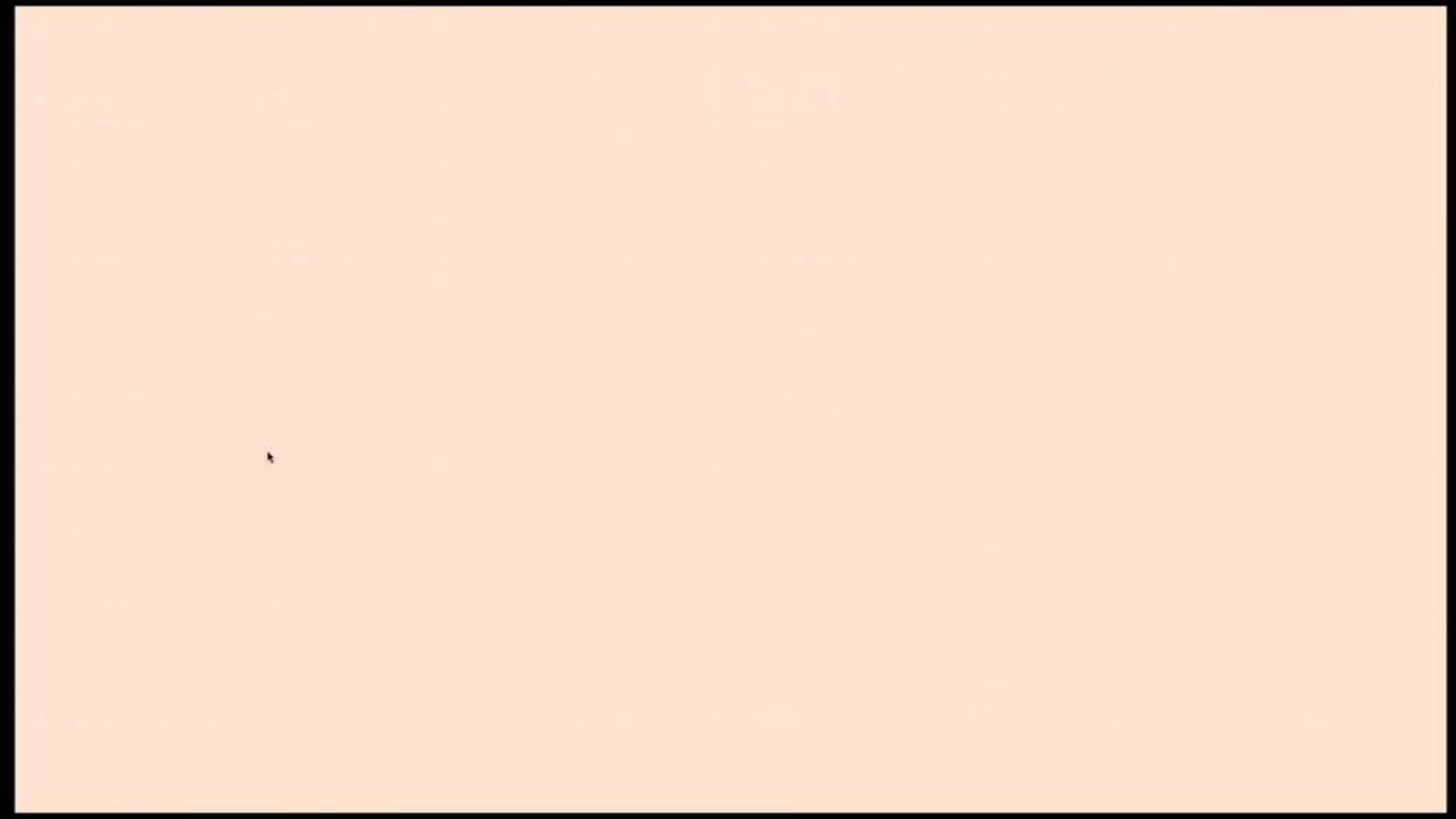














# **Notebook file format**

Notebooks are stored on disk as JSON files. JSON is a really simple way of representing data: it looks exactly like Python lists and dictionaries, so you already know how to read it.

```
{
  "key": "value",
  "ultimate answer": 42,
  "lists": ["like", "this"]
}
```

At the top level of the notebook file there are four fields:

 nbformat & nbformat\_minor: The version of the format this notebook is stored in. The current version is 4.1. Insert

View

File

Edit

```
"key": "value",

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```

Cell

At the top level of the notebook file there are four fields:

Kernel

 nbformat & nbformat\_minor: The version of the format this notebook is stored in. The current version is 4.1.

Widgets

Help

- metadata: Information about the notebook, like the language it's written in.
- · cells: List of cells with the notebook content

## Challenges

Open the notebooks in this directory in your text editor and look at the structure.

- 1. What distinguishes a markdown cell from a code cell?
- 2. How many different kinds of output can you see?

The <u>notebook format documentation</u> has the answers. It describes the structure of notebook files in detail.



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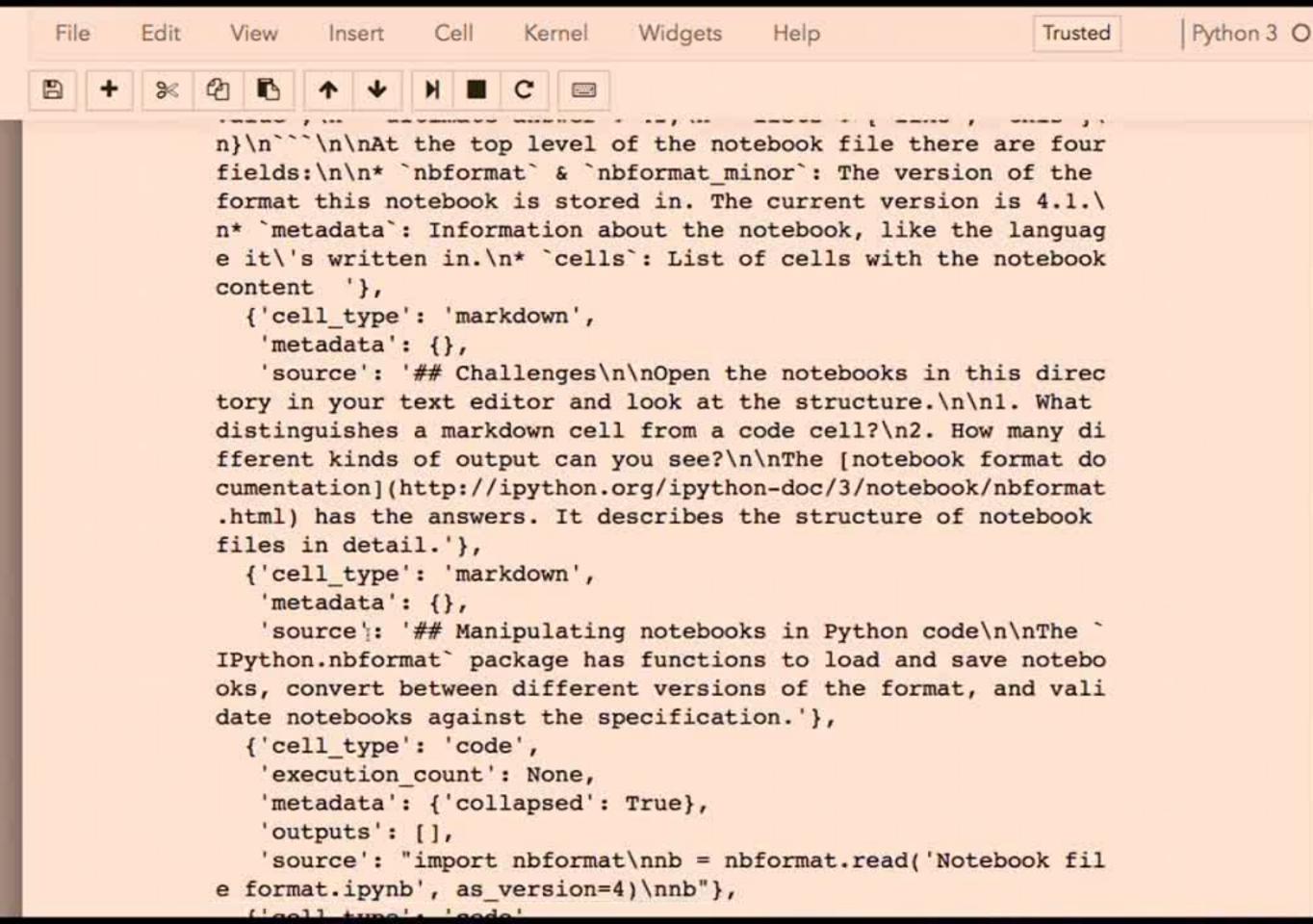
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```
In [5]: import nbformat
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        nb
Out[5]: {'cells': [{'cell type': 'markdown',
           'metadata': {},
           'source': '# Notebook file format\n\nNotebooks are stored on
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{'cell type': 'code',

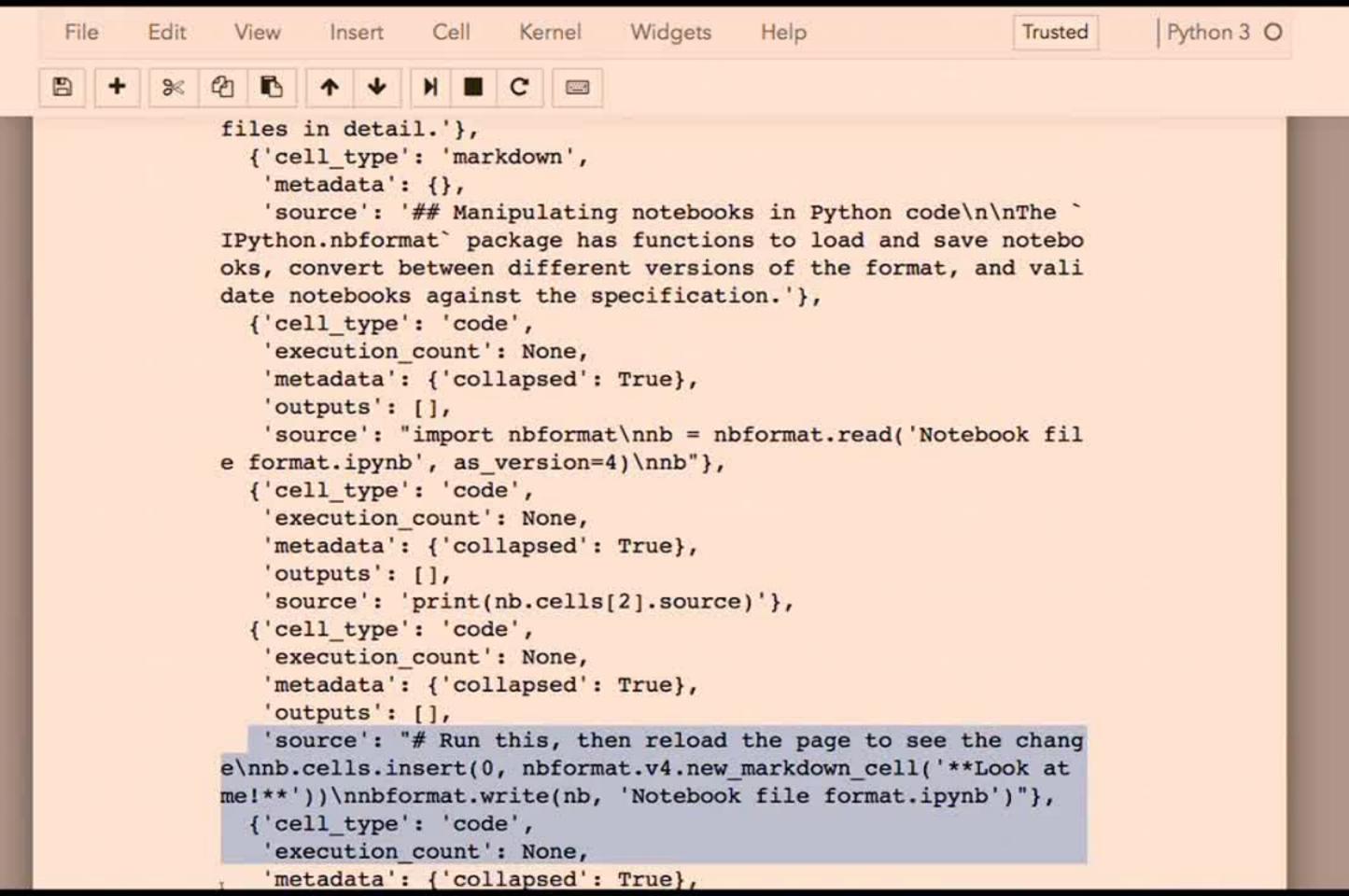
I 'source': "# Run this, then reload the page to see the chang

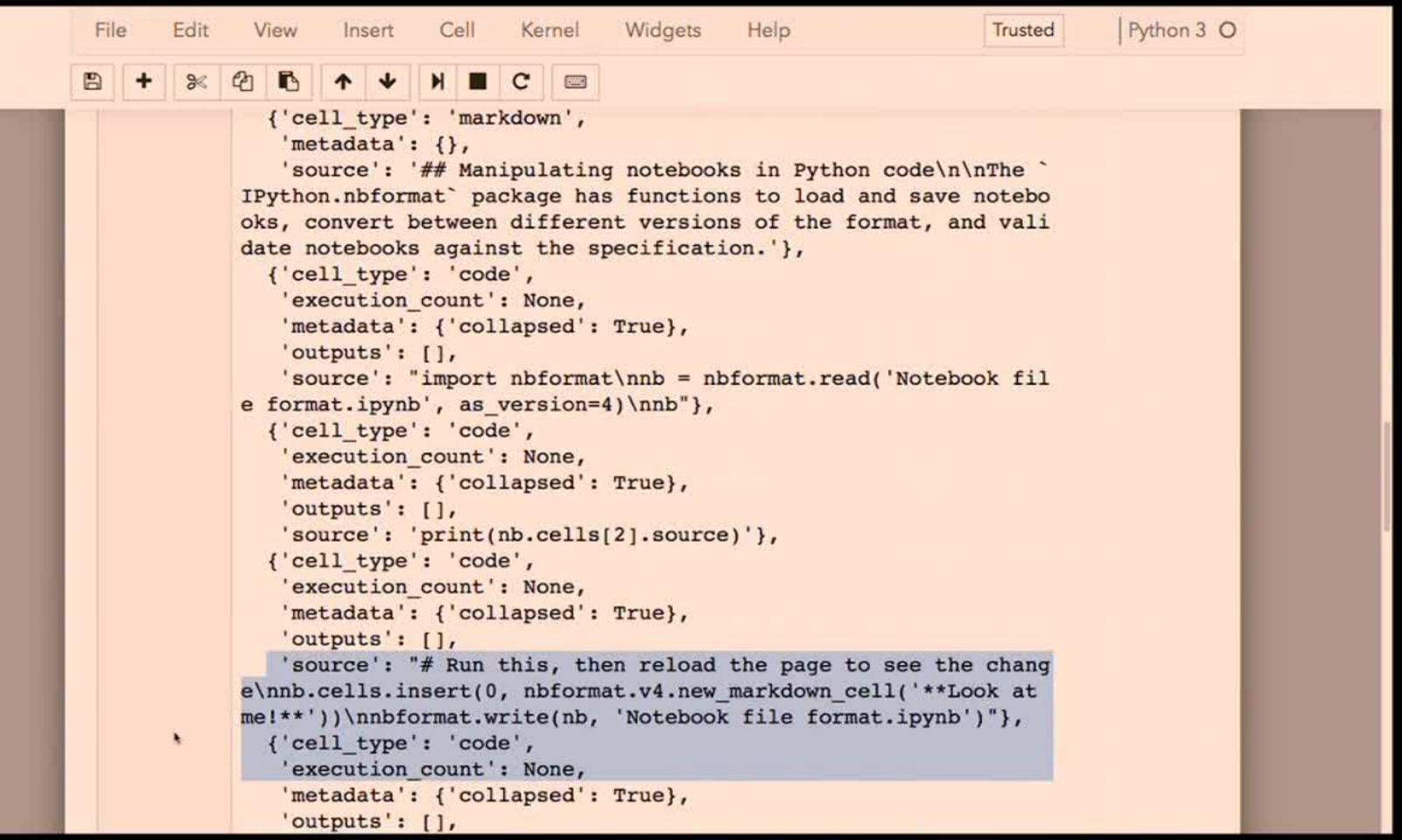
e\nnb.cells.insert(0, nbformat.v4.new markdown cell('\*\*Look at

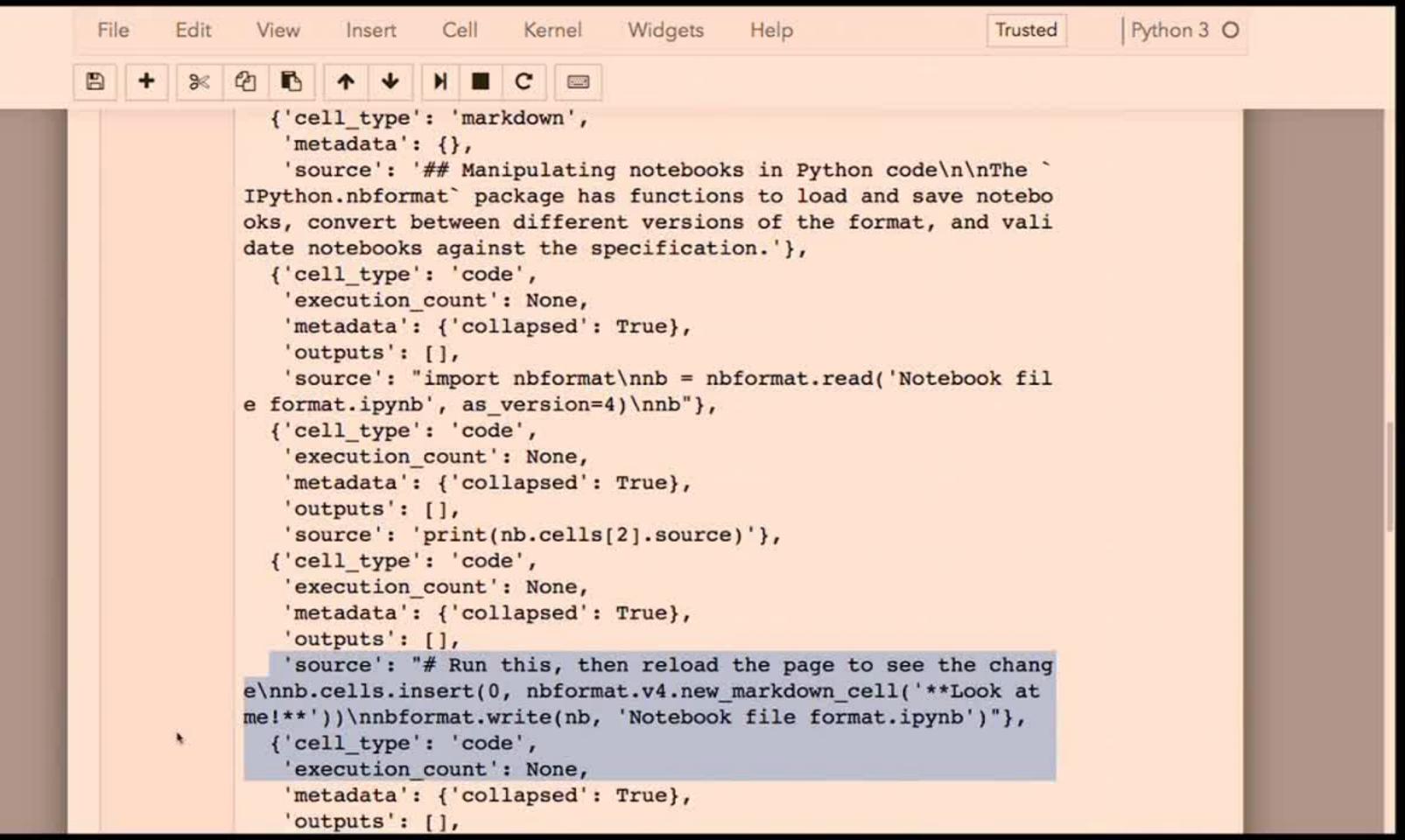
me!\*\*'))\nnbformat.write(nb, 'Notebook file format.ipynb')"},

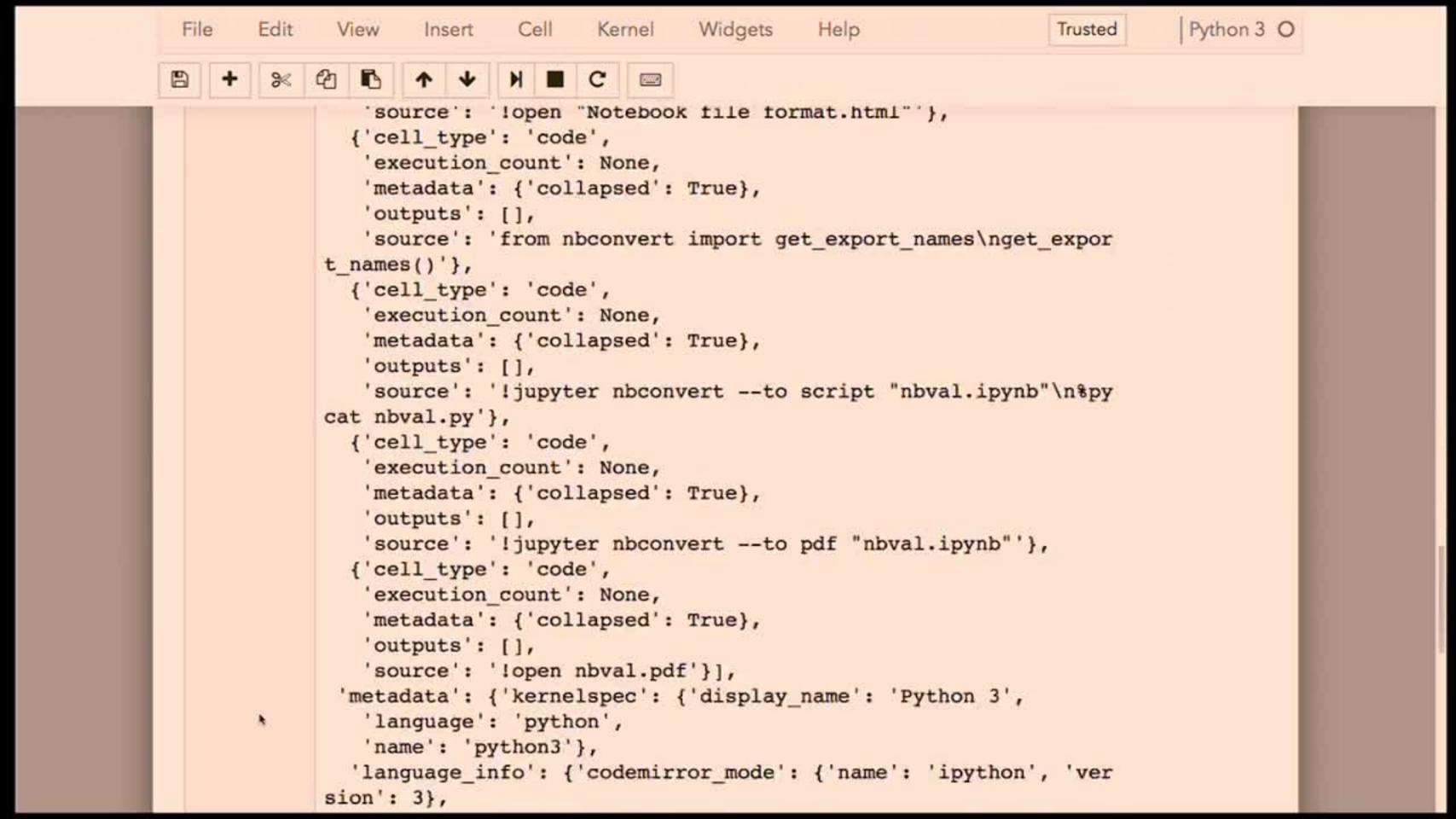
{'cell type': 'code',

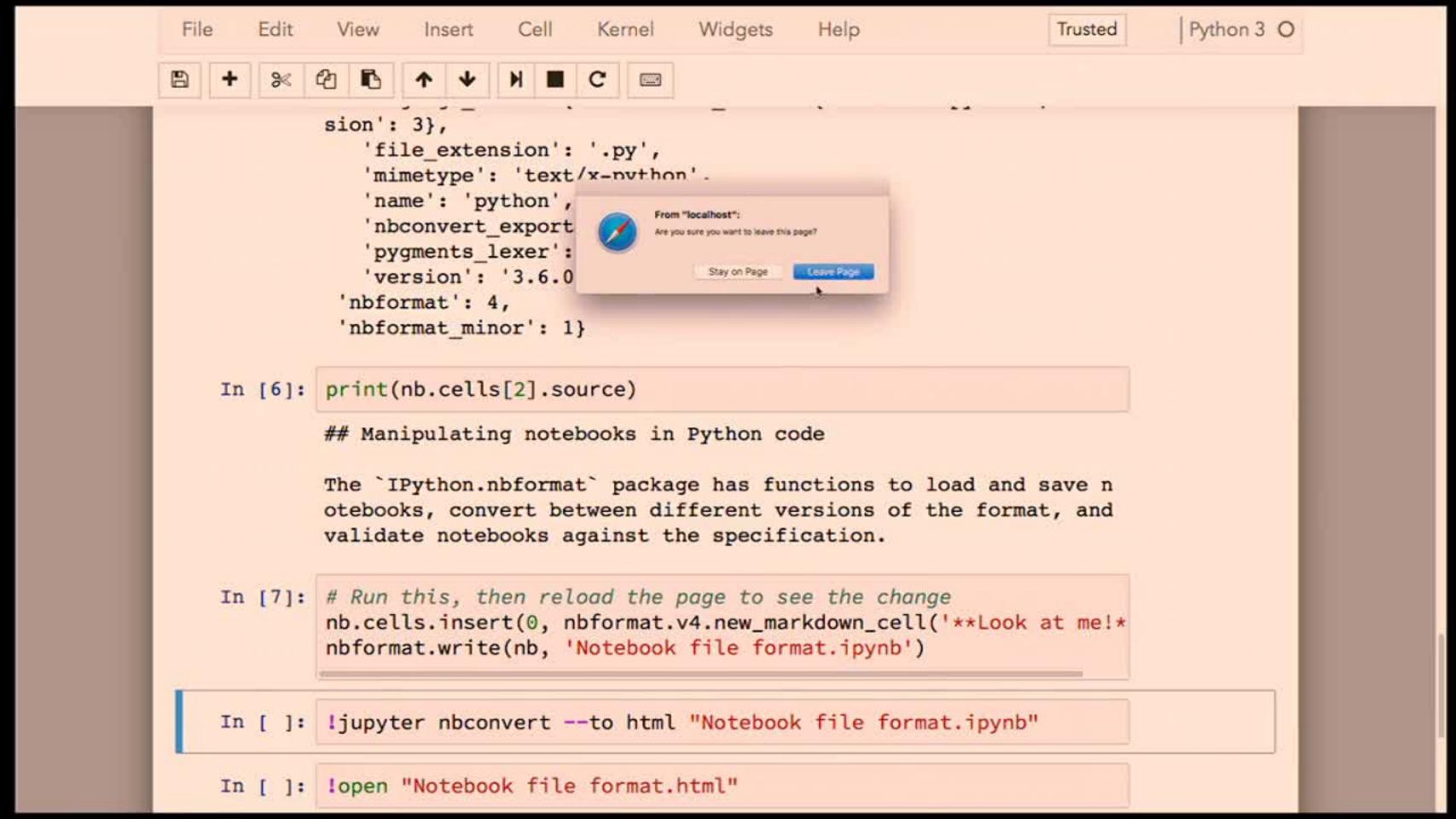
'execution count': None,

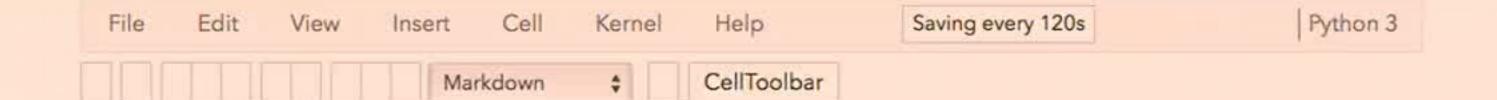












Look at me!

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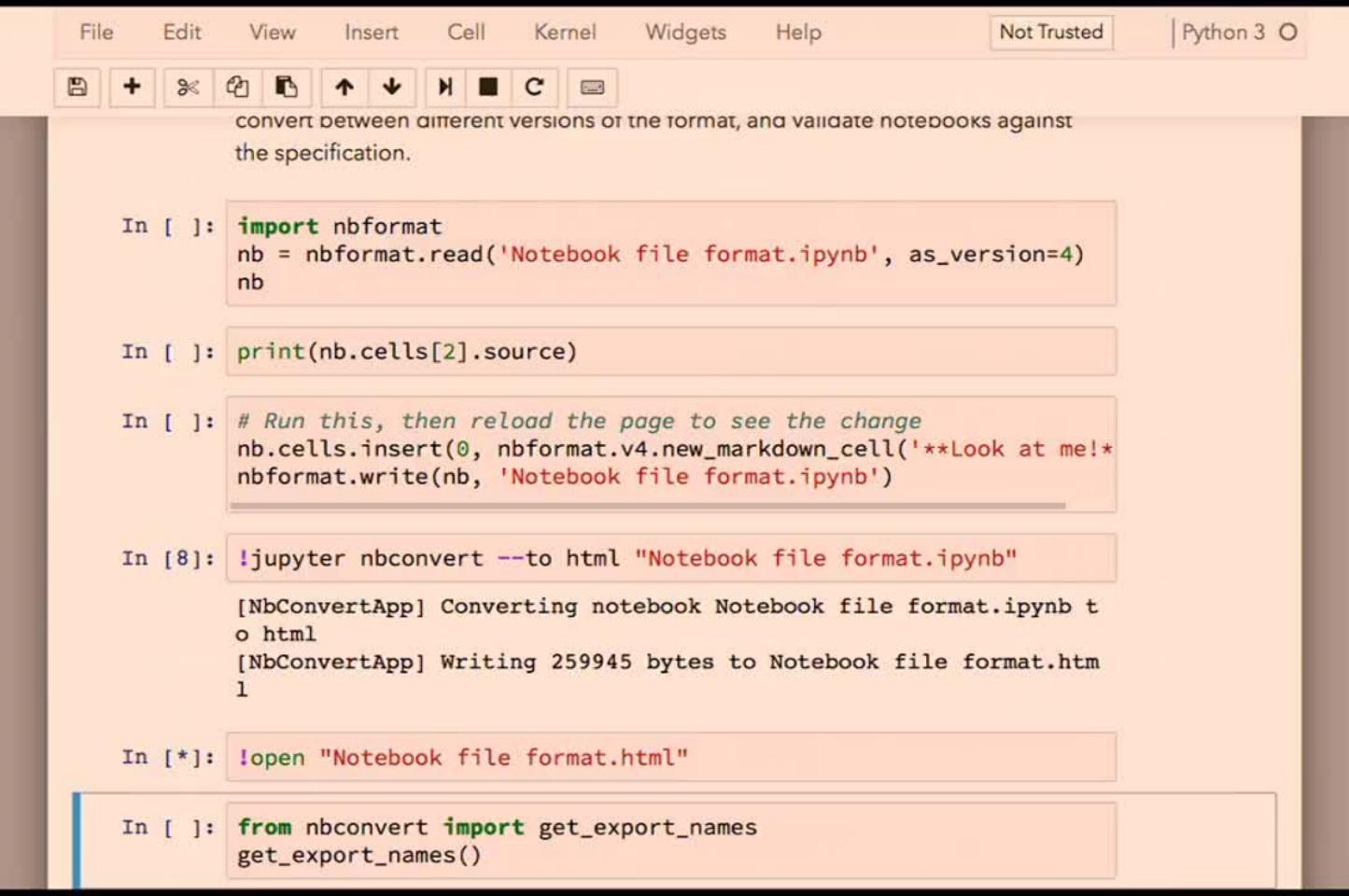
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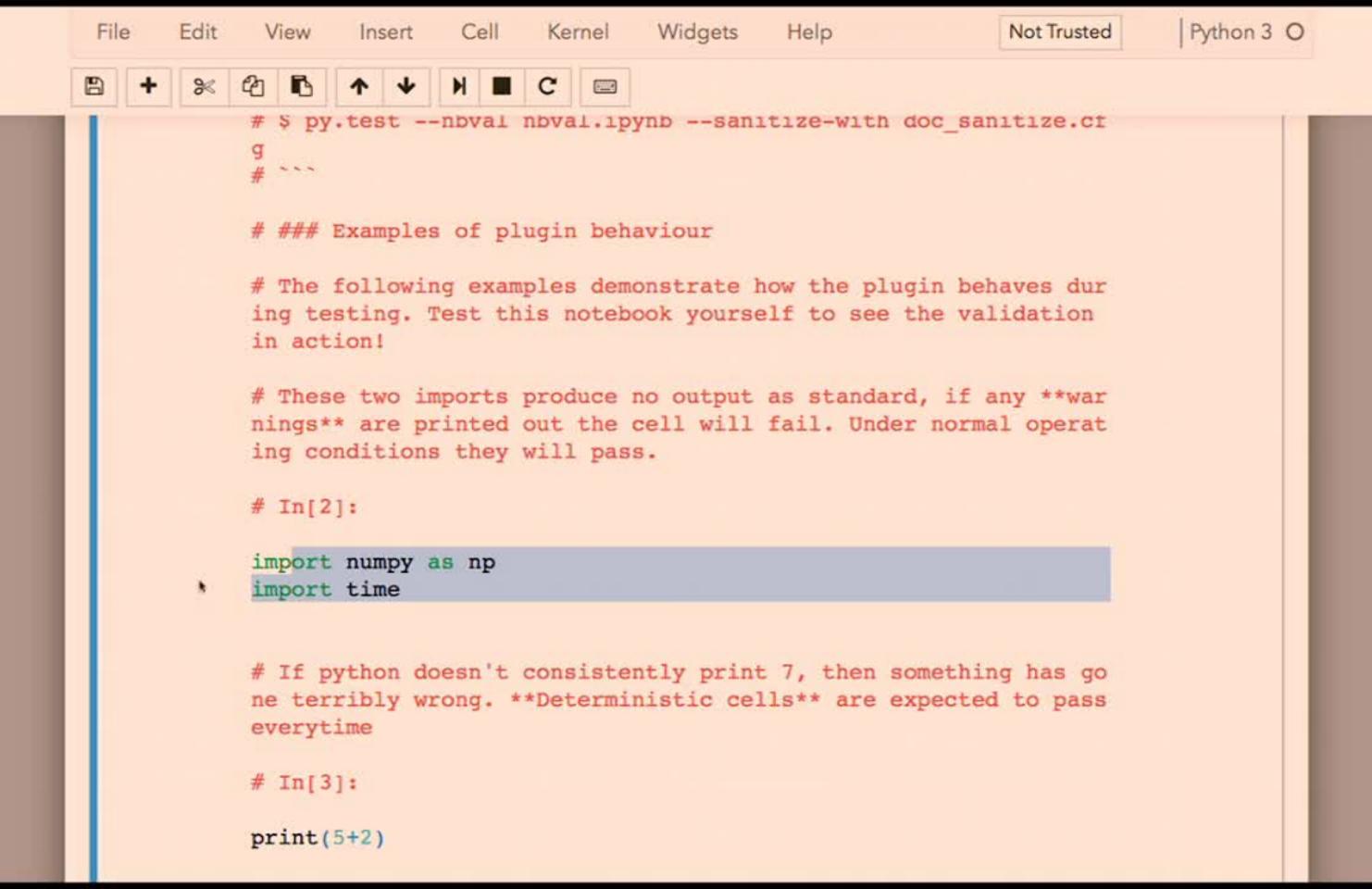
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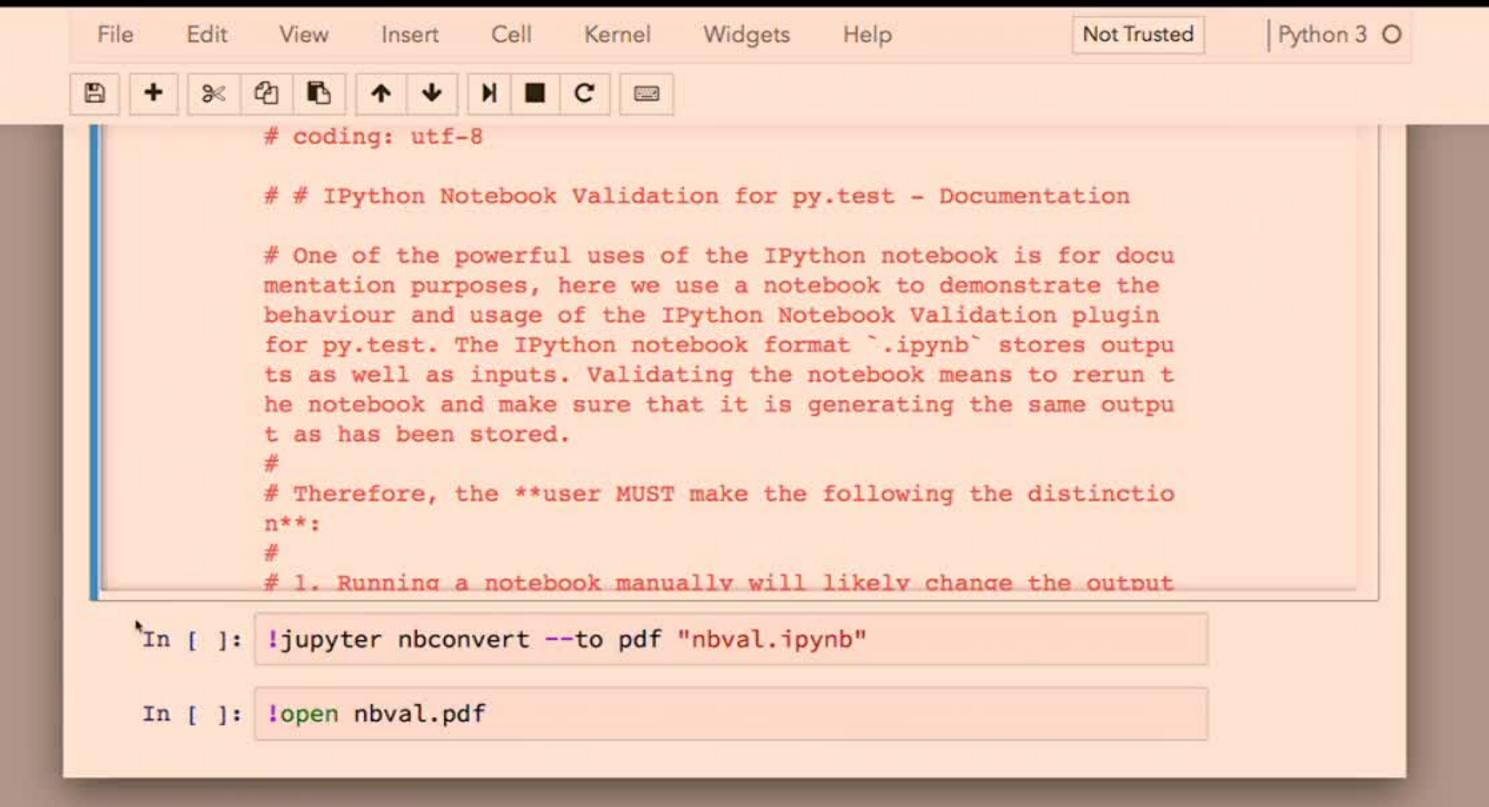
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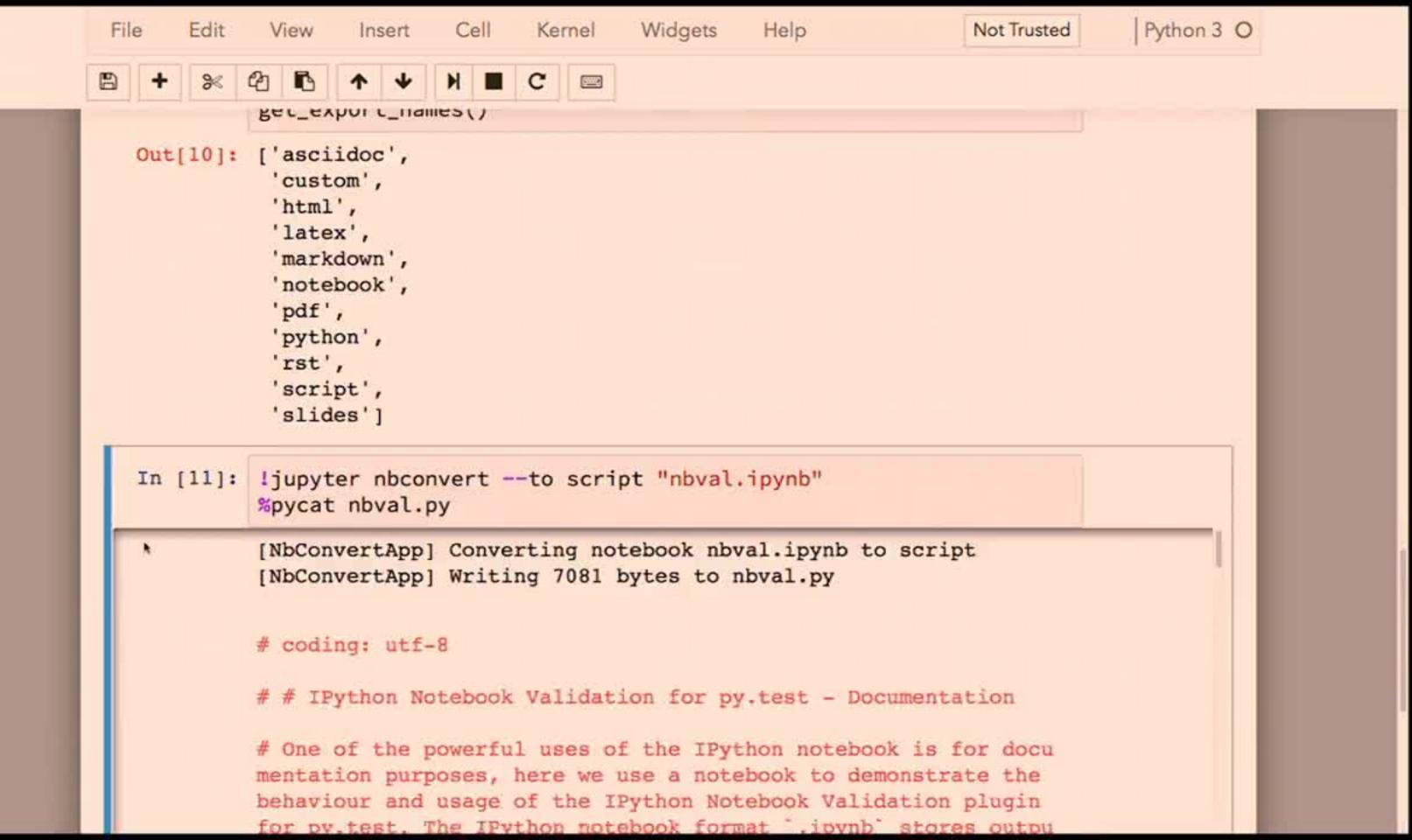
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nbformat.write(nb, Notebook file format.ipyn
        b')
In [ ]: !jupyter nbconvert --to html "Notebook file f
        ormat.ipynb"
In [ ]: !open "Notebook file format.html"
In [ ]: from nbconvert import get export names
        get export names()
In [ ]: !jupyter nbconvert --to script "nbval.ipynb"
        %pycat nbval.py
In [ ]: !jupyter nbconvert --to pdf "nbval.ipynb"
In [ ]: !open nbval.pdf
```

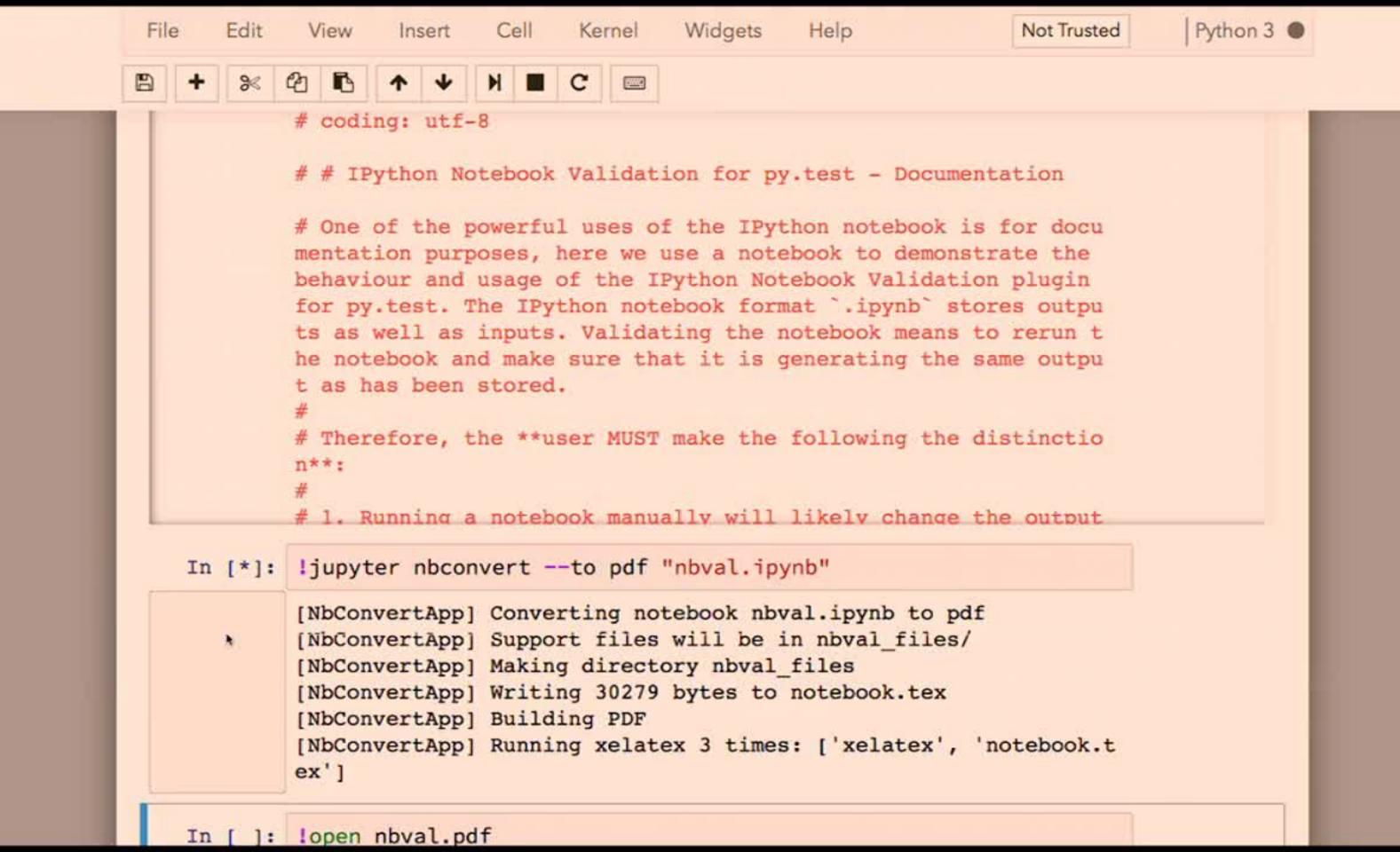
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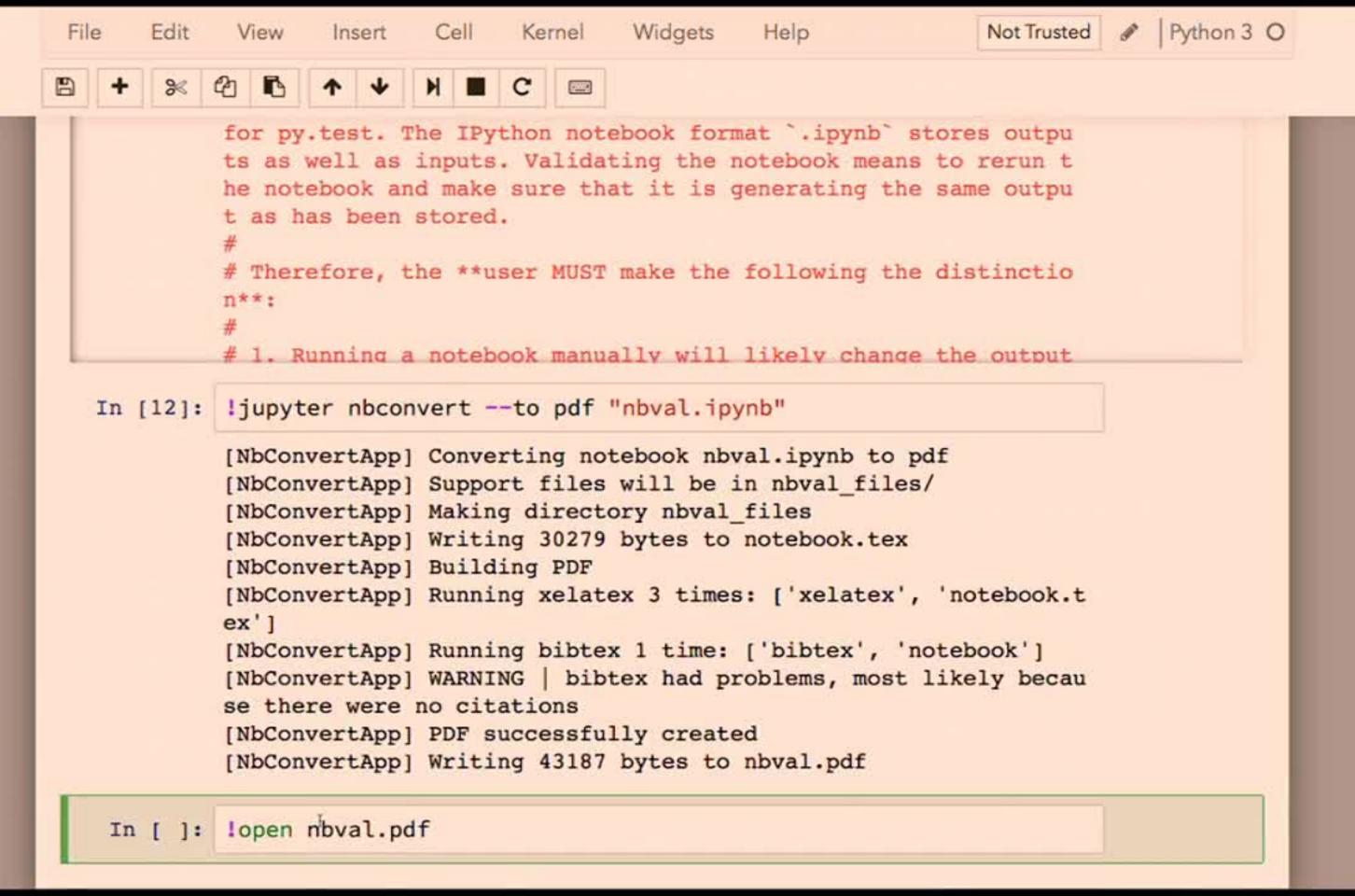


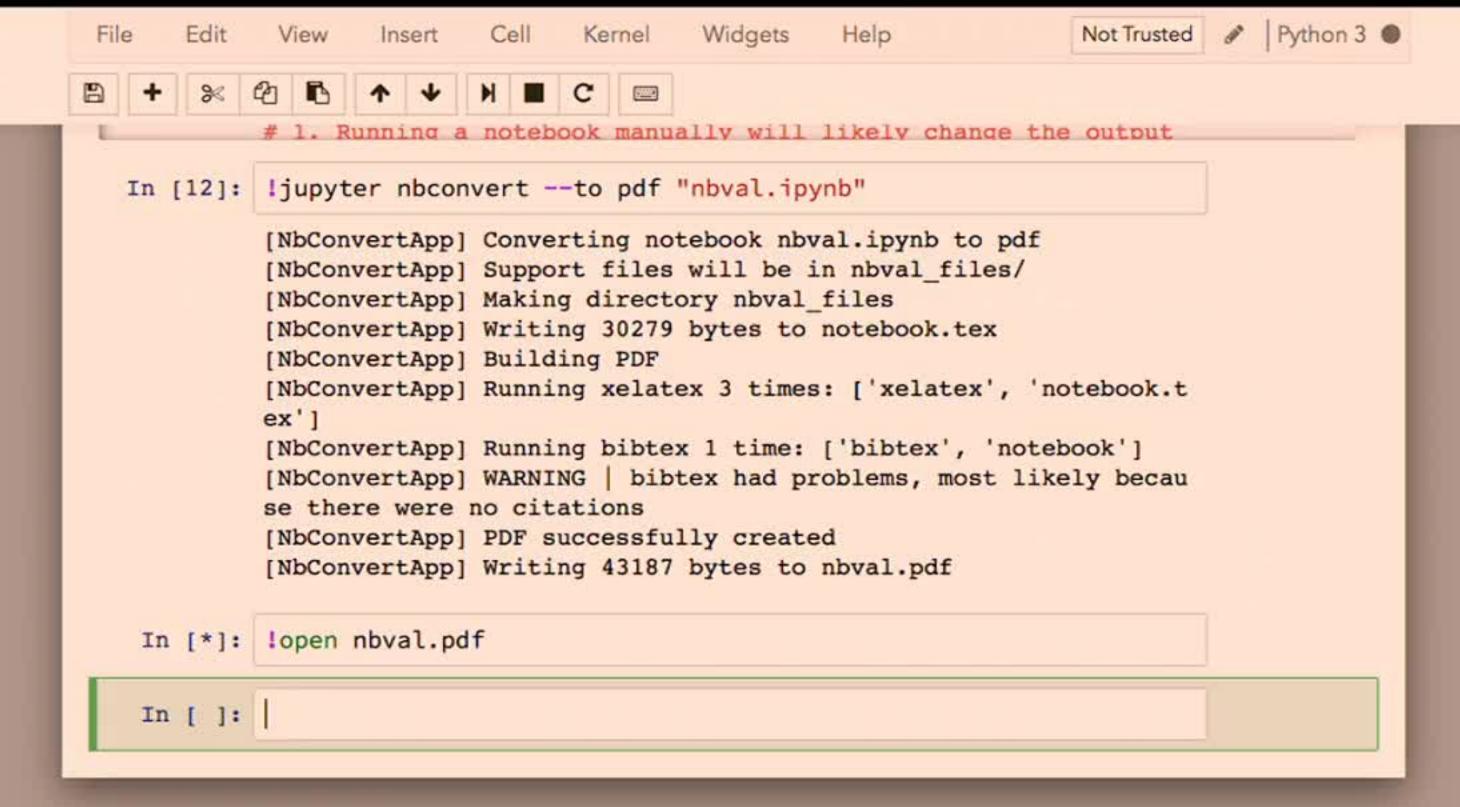




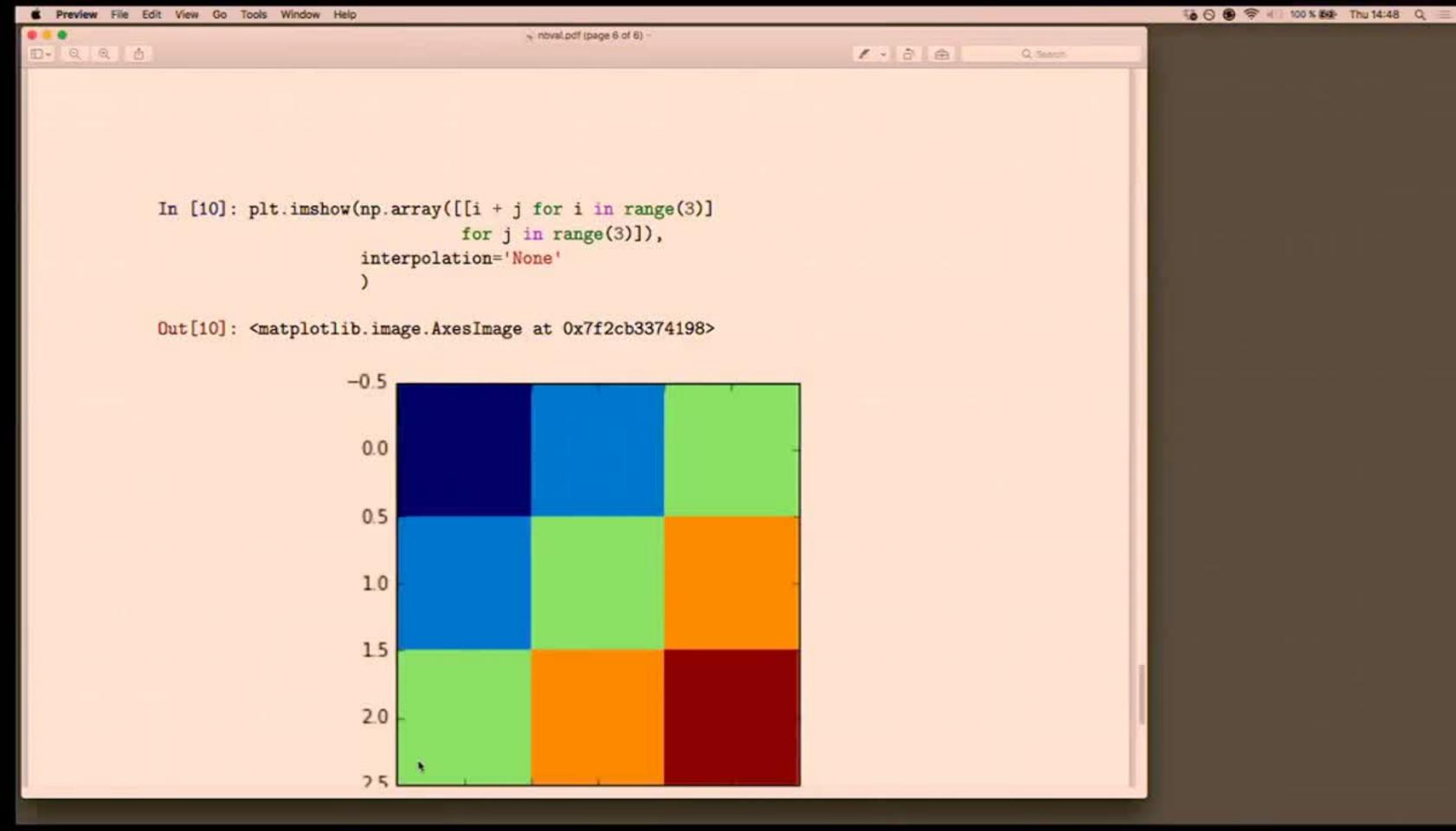


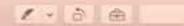






In [ ]:

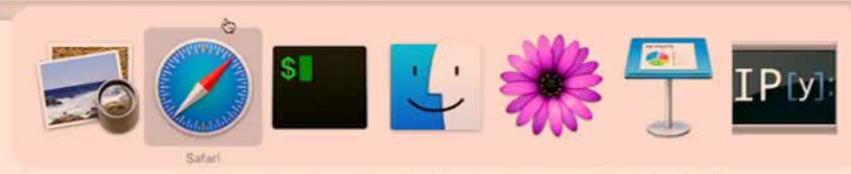




Q Search

If the raised exception doesn't match the stored exception, we get a failure

4



RuntimeError

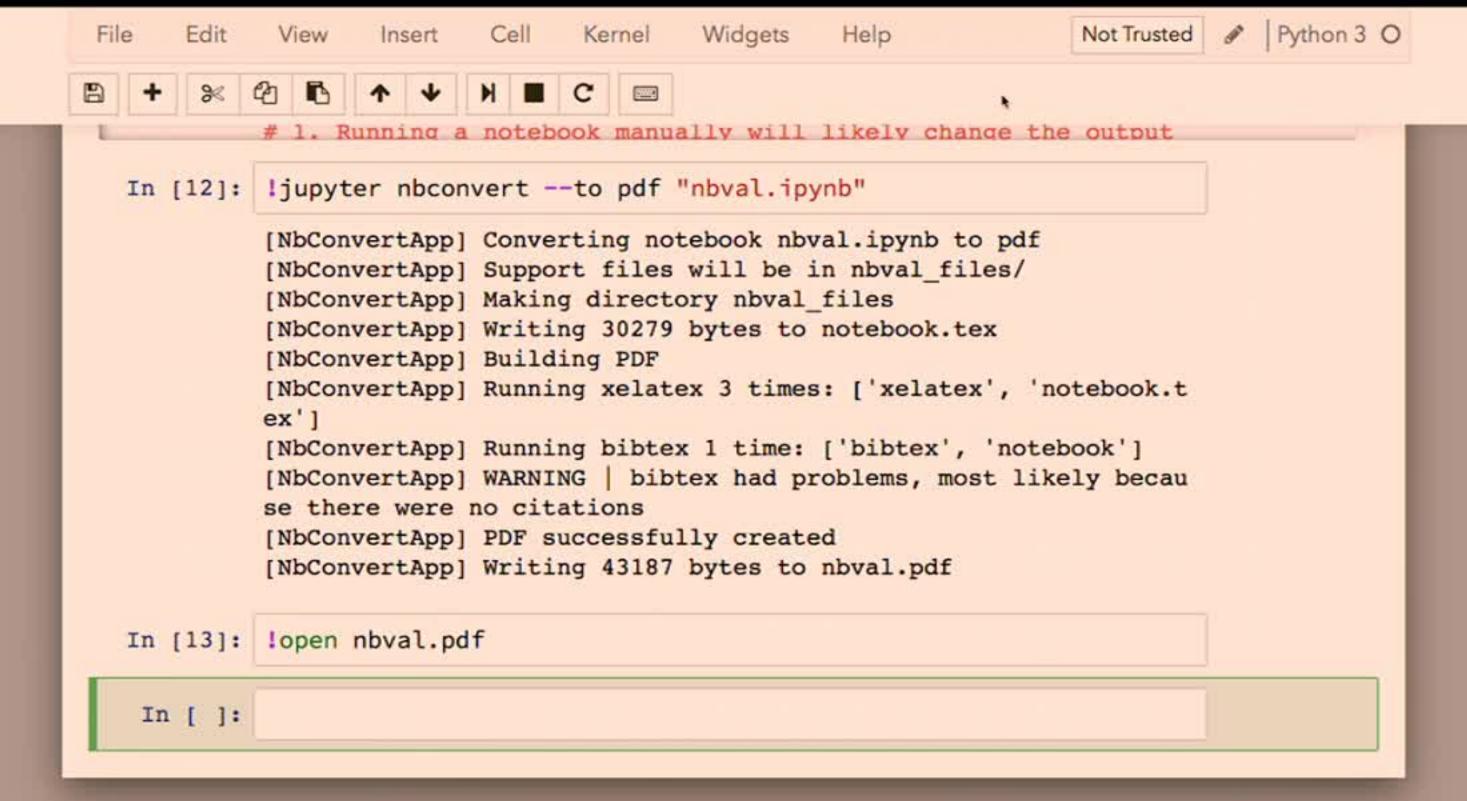
Traceback (most recent call last)

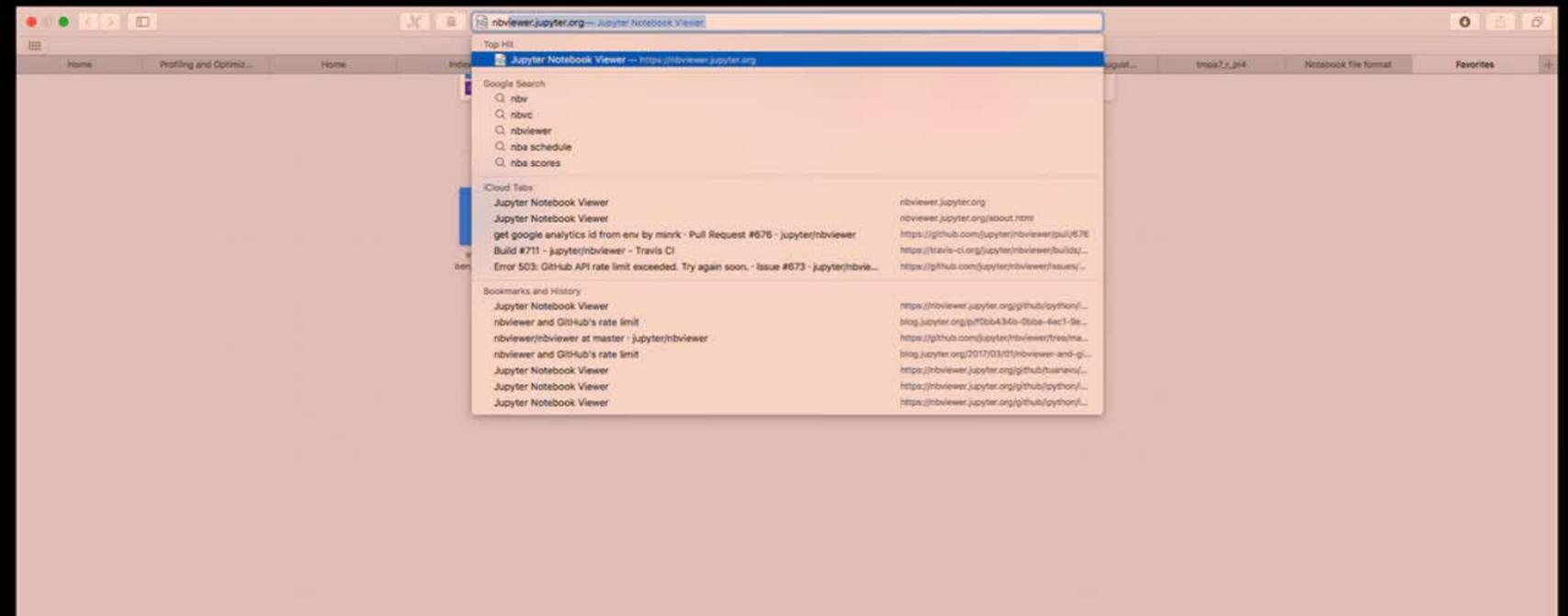
<ipython-input-3-32dcc1c70a4e> in <module>()

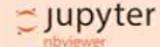
- 1 # NBVAL\_RAISES\_EXCEPTION
- 2 print("If the raised exception doesn't match the stored exception, we get a failure"
- ---> 3 raise RuntimeError("Foo")

RuntimeError: Foo

In [2]: # NBVAL\_IGNORE\_OUTPUT







# nbviewer

A simple way to share Jupyter Notebooks

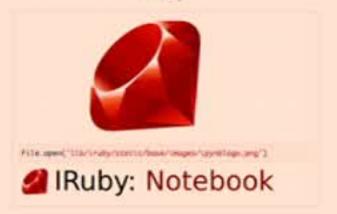
minrk Gol

### **Programming Languages**

**IPython** 



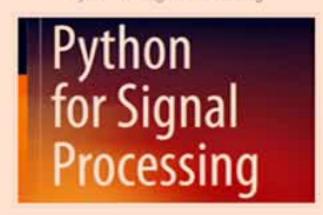
(Ruby



**Uula** 



Python for Signal Processing



**Books** 

O'Relly Book



Probabilistic Programming









ipython-cse17 Notebook file format.ipynb

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ipython-cse17 / Beyond Plain Python.ipynb

jupyter

# IPython: beyond plain Python

When executing code in IPython, all valid Python syntax works as-is, but IPython provides a number of features designed to make the interactive experience more fluid and efficient.

# First things first: running code, getting help

In the notebook, to run a cell of code, hit Shift-Enter. This executes the cell and puts the cursor in the next cell below, or makes a new one if you are at the end.

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In [1]: print("Hi")
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IPython -- An enhanced Interactive Python
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The ?/?? system gives access to the full source code for any object (if available), shows function prototypes and other useful information.

If you just want to see an object's docstring, type '%pdoc object' (without quotes, and without % if you have automagic on).

\* Tab completion in the local namespace:

At any time, hitting tab will complete any available python commands or variable names, and show you a list of the possible completions if there's no unambiguous one. It will also complete filenames in the current directory.

- \* Search previous command history in multiple ways:
  - Start typing, and then use arrow keys up/down or (Ctrl-p/Ctrl-n) to search through the history items that match what you've typed so far.
  - Hit Ctrl-r: opens a search prompt. Begin typing and the system searches your history for lines that match what you've typed so far, completing as much as it can.

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- \* Search previous command history in multiple ways:
  - Start typing, and then use arrow keys up/down or (Ctrl-p/Ctrl-n) to search through the history items that match what you've typed so far.
  - Hit Ctrl-r: opens a search prompt. Begin typing and the system searches your history for lines that match what you've typed so far, completing as much as it can.

All father assembly hilled a new how far down

- \* Access to the standard Python help with object docstrings and the Python manuals. Simply type 'help' (no quotes) to invoke it.
- \* Magic commands: type %magic for information on the magic subsystem.
- \* System command aliases, via the %alias command or the configuration file(s).
- \* Dynamic object information:

Typing ?word or word? prints detailed information about an object. Certain long strings (code, etc.) get snipped in the center for brevity.

Typing ??word or word?? gives access to the full information without snipping long strings. Strings that are longer than the screen are printed through the less pager.

The ?/?? system gives access to the full source code for any object (if available), shows function prototypes and other useful information.

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  - %hist: search history by index.
- \* Persistent command history across sessions.
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- \* Persistent command history across sessions.
- \* Logging of input with the ability to save and restore a working session.
- \* System shell with !. Typing !ls will run 'ls' in the current directory.
- \* The reload command does a 'deep' reload of a module: changes made to the module since you imported will actually be available without having to exit.







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\* Output caching system:

For output that is returned from actions, a system similar to the input cache exists but using \_ instead of \_i. Only actions that produce a result (NOT assignments, for example) are cached. If you are familiar with Mathematica, IPython's \_ variables behave exactly like Mathematica's % variables.

The following GLOBAL variables always exist (so don't overwrite them!):
\_ (one underscore): previous output.
\_ (two underscores): next previous.
\_ (three underscores): next-next previous.

Global variables named \_<n> are dynamically created (<n> being the prompt counter), such that the result of output <n> is always available as \_<n>.

Finally, a global dictionary named \_oh exists with entries for all lines which generated output.

\* Directory history:

Your history of visited directories is kept in the global list \_dh, and the magic %cd command can be used to go to any entry in that list.

- \* Auto-parentheses and auto-quotes (adapted from Nathan Gray's LazyPython)
  - Auto-parentheses

Callable objects (i.e. functions, methods, etc) can be invoked like this (notice the commas between the arguments)::

In [1]: callable\_ob arg1, arg2, arg3

and the input will be translated to this::

callable ob(argl, arg2, arg3)

This feature is off by default (in rare cases it can produce undesirable side-effects), but you can activate it at the command-line by starting IPython with `--autocall 1`, set it permanently in your configuration file, or turn on at runtime with `%autocall 1`.

You can force auto-parentheses by using '/' as the first character

```
of a line. For example::
       In [1]: /globals
                                  # becomes 'globals()'
  Note that the '/' MUST be the first character on the line! This
  won't work::
       In [2]: print /globals # syntax error
  In most cases the automatic algorithm should work, so you should
  rarely need to explicitly invoke /. One notable exception is if you
  are trying to call a function with a list of tuples as arguments (the
  parenthesis will confuse IPython)::
       In [1]: zip (1,2,3), (4,5,6) # won't work
  but this will work::
       In [2]: /zip (1,2,3),(4,5,6)
       ----> zip ((1,2,3),(4,5,6))
       Out[2] = [(1, 4), (2, 5), (3, 6)]
  IPython tells you that it has altered your command line by
  displaying the new command line preceded by -->. e.g.::
       In [18]: callable list
       ----> callable (list)
2. Auto-Quoting
  You can force auto-quoting of a function's arguments by using ',' as
  the first character of a line. For example::
       In [1]: ,my_function /home/me # becomes my_function("/home/me")
  If you use ';' instead, the whole argument is quoted as a single
  string (while ',' splits on whitespace)::
       In [2]: ,my function a b c # becomes my function("a", "b", "c")
       In [3]: ;my function a b c # becomes my function("a b c")
  Note that the ',' MUST be the first character on the line! This
   won't work::
```

```
In [2]: /zip (1,2,3),(4,5,6)
       ----> zip ((1,2,3),(4,5,6))
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       In [3]: ;my function a b c # becomes my function("a b c")
  Note that the ',' MUST be the first character on the line! This
  won't work::
       In [4]: x = ,my function /home/me # syntax error
```

Typing object\_name? will print all sorts of details about any object, including docstrings, function definition lines (for call arguments) and constructor details for classes.

```
In [3]: import pandas as pd
pd.DataFrame?

Init signature: pd.DataFrame(data=None, index=None, columns=None, dtype=None, copy=False)
Docstring:
```

Two-dimensional size-mutable, potentially heterogeneous tabular data structure with labeled axes (rows and columns). Arithmetic operations align on both row and column labels. Can be thought of as a dict-like container for Series objects. The primary pandas data structure

```
>>> df = DataFrame(data=d, index=index)
        >>> df2 = DataFrame(np.random.randn(10, 5))
        >>> df3 = DataFrame(np.random.randn(10, 5),
                            columns=['a', 'b', 'c', 'd', 'e'])
        ...
        See also
        DataFrame.from records : constructor from tuples, also record arrays
        DataFrame.from dict : from dicts of Series, arrays, or dicts
        DataFrame.from items : from sequence of (key, value) pairs
        pandas.read csv, pandas.read table, pandas.read clipboard
                        -/conda/lib/python3.6/site-packages/pandas/core/frame.py
        File:
        Type:
                        type
        Using two question marks will try to find the source code for the given object.
In [4]: pd.DataFrame??
        Init signature: pd.DataFrame(data=None, index=None, columns=None, dtype=None, copy=False)
        Source:
        class DataFrame (NDFrame):
            """ Two-dimensional size-mutable, potentially heterogeneous tabular data
            structure with labeled axes (rows and columns). Arithmetic operations
            align on both row and column labels. Can be thought of as a dict-like
            container for Series objects. The primary pandas data structure
            Parameters
            data : numpy ndarray (structured or homogeneous), dict, or DataFrame
                Dict can contain Series, arrays, constants, or list-like objects
            index : Index or array-like
                Index to use for resulting frame. Will default to np.arange(n) if
                no indexing information part of input data and no index provided
            columns : Index or array-like
                Column labels to use for resulting frame. Will default to
                np.arange(n) if no column labels are provided
            dtype : dtype, default None
                Data type to force, otherwise infer
            copy : boolean, default False
                Copy data from inputs. Only affects DataFrame / 2d ndarray input
```

>>> d = { coll : tsl, coll : ts2}

```
pandas.read csv, pandas.read table, pandas.read clipboard
                        ~/conda/lib/python3.6/site-packages/pandas/core/frame.py
        File:
        Type:
        Using two question marks will try to find the source code for the given object.
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            copy : boolean, default False
                Copy data from inputs. Only affects DataFrame / 2d ndarray input
            Examples
            >>> d = {'col1': ts1, 'col2': ts2}
            >>> df = DataFrame(data=d, index=index)
            >>> df2 = DataFrame(np.random.randn(10, 5))
            >>> df3 = DataFrame(np.random.randn(10, 5),
                                columns=['a', 'b', 'c', 'd', 'e'])
             ...
             See also
```

DataFrame from records a constructor from tunles, also record array









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### Command line usage

The py.test program doesn't usually collect notebooks for testing; by passing the --nbval flag at the command line, the IPython Notebook Validation plugin will collect and test notebook cells, comparing their outputs with those saved in the file.

```
$ py.test --nbval my notebook.ipynb
```

There is also an option --nbval-lax, which collects notebooks and runs them, failing if there is an error. This mode does not check the output of cells unless they are marked with a special #NBVAL CHECK OUTPUT comment.









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```
$ py.test --nbval-lax my_notebook.ipynb
```

# REGEX Output sanitizing

Since all output is captured by the IPython notebook, some pesky messages and prompts (with time-stamped messages, for example) may fail tests always, which might be expected. The plugin allows the user to specify a sanitizing file at the command prompt using the following flag:

```
$ py.test --nbval my_notebook.ipynb --sanitize-with my_sanitize_file
```

This sanitize file contains a number of REGEX replacements. It is recommended, when removing output for the tests, that you replace the removed output with some sort of marker, this helps with debugging. The following file is written to the folder of this notebook and can be used to santize its outputs:

```
In [1]: %%writefile doc sanitize.cfg
        [regex1]
        regex: \d{1,2}/\d{1,2}/\d{2,4}
        replace: DATE-STAMP
        [regex2]
        regex: \d{2}:\d{2}:\d{2}
        replace: TIME-STAMP
```

```
$ cd /path/to/this/notebook
$ py.test --nbval nbval.ipynb --sanitize-with doc_sanitize.cfg
```

### Examples of plugin behaviour

The following examples demonstrate how the plugin behaves during testing. Test this notebook yourself to see the validation in action!

These two imports produce no output as standard, if any warnings are printed out the cell will fail. Under normal operating conditions they will pass.

```
In [2]: import numpy as np import time I
```

If python doesn't consistently print 7, then something has gone terribly wrong. Deterministic cells are expected to pass everytime

```
In [3]: print(5+2)
7
```

Random outputs will always fail.

```
In [4]: print([np.random.rand() for i in range(4)])
    print([np.random.rand() for i in range(4)])

[0.36133679016382714, 0.5043774697891126, 0.23281910875007927, 0.2713065513128683]
[0.5512421277985322, 0.02592706358897756, 0.05036036771084684, 0.7515926759190724]
```

Inconsistent number of lines of output will cause an error to be thrown.

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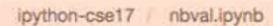
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[0.5512421277985322, 0.02592706358897756, 0.05036036771084684, 0.7515926759190724]
```

Inconsistent number of lines of output will cause an error to be thrown.

```
In [5]: for i in range(np.random.randint(1, 8)):
    print(1)
```







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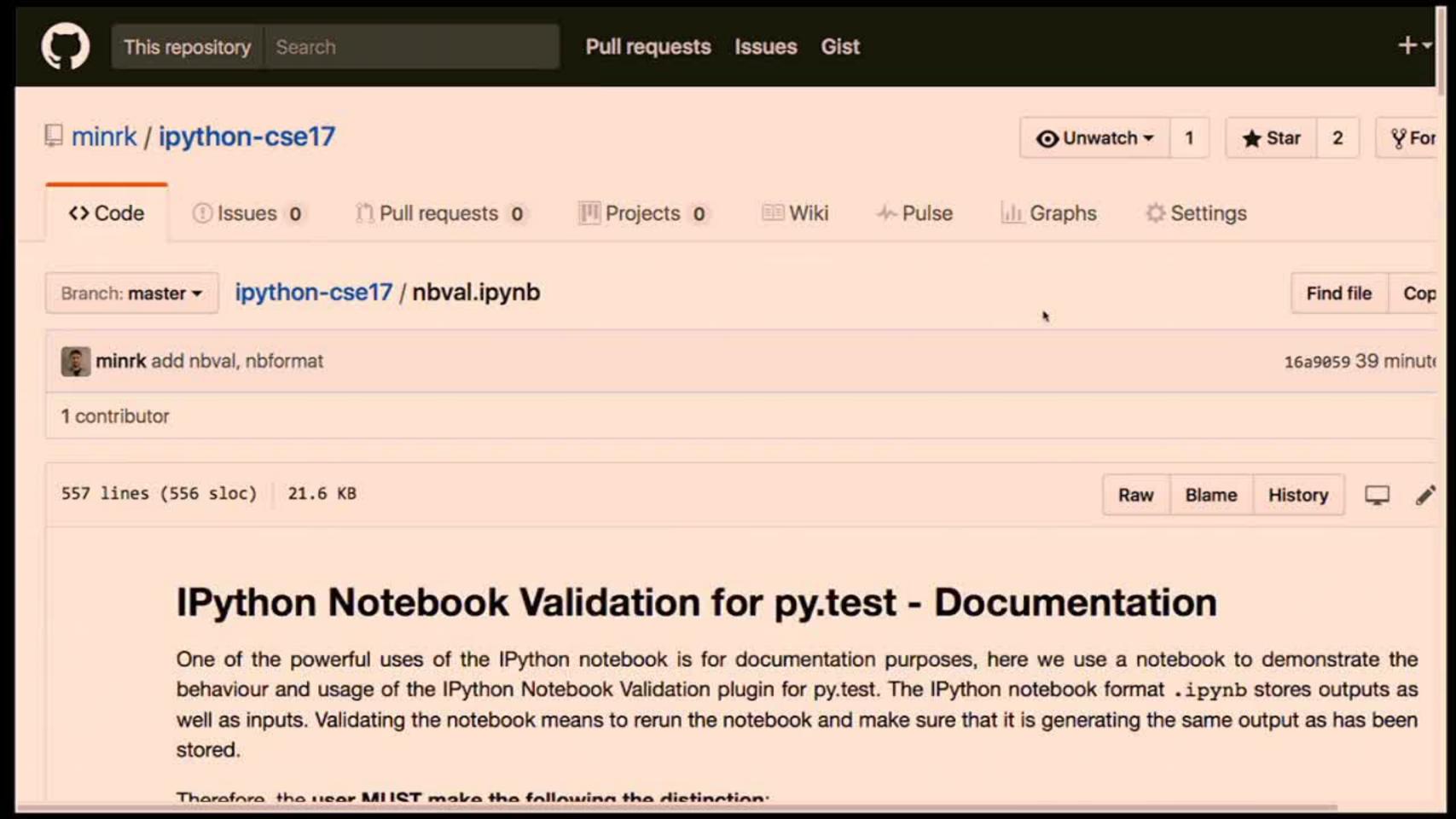
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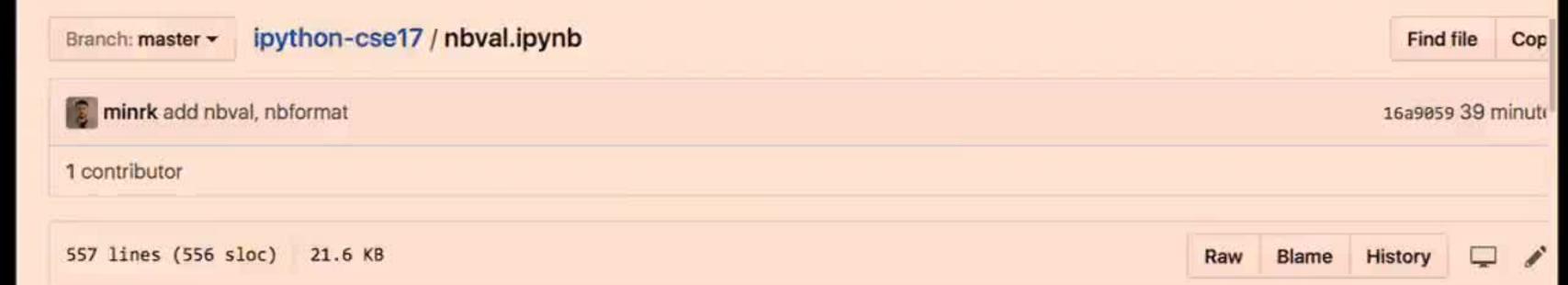




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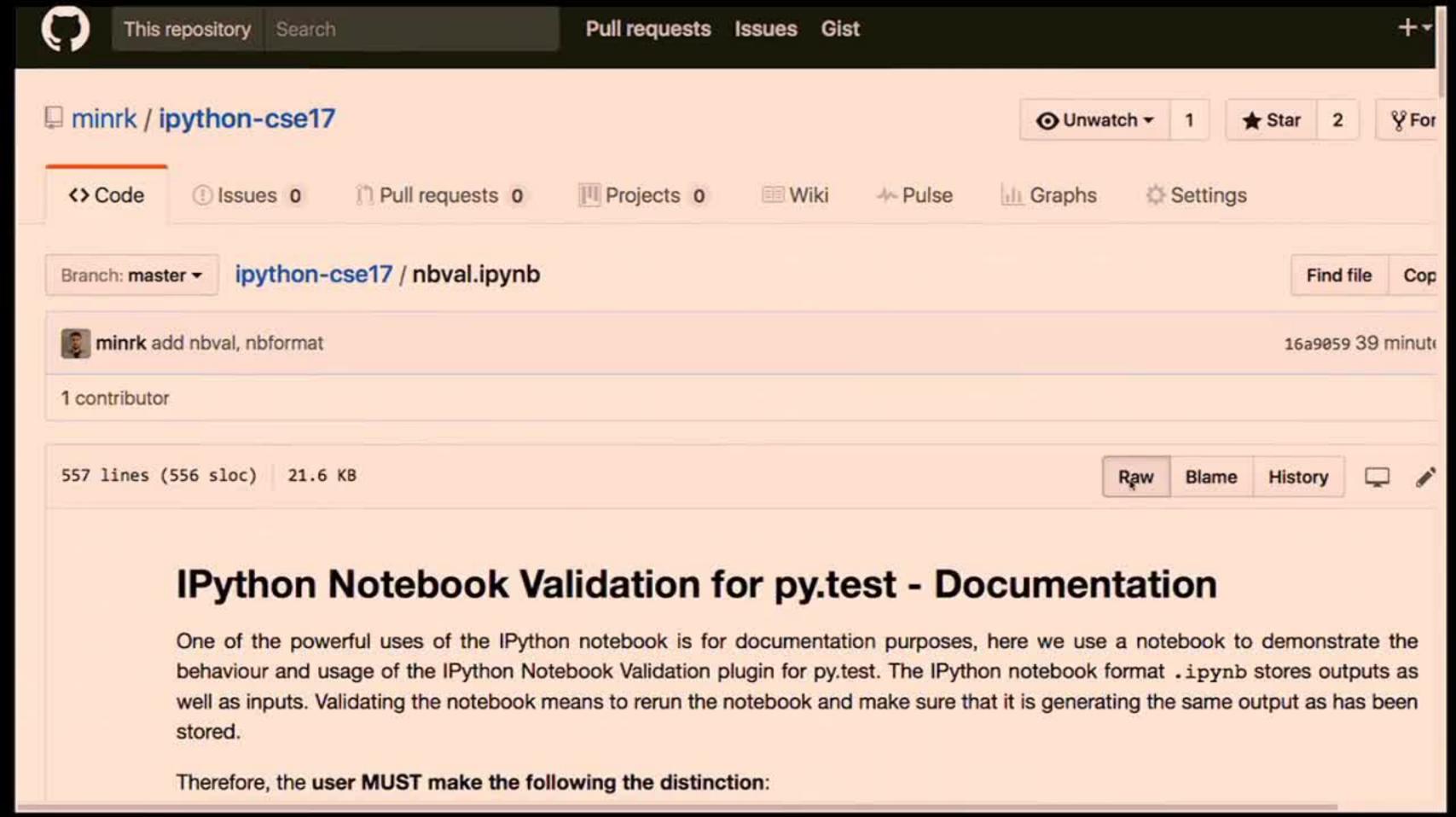
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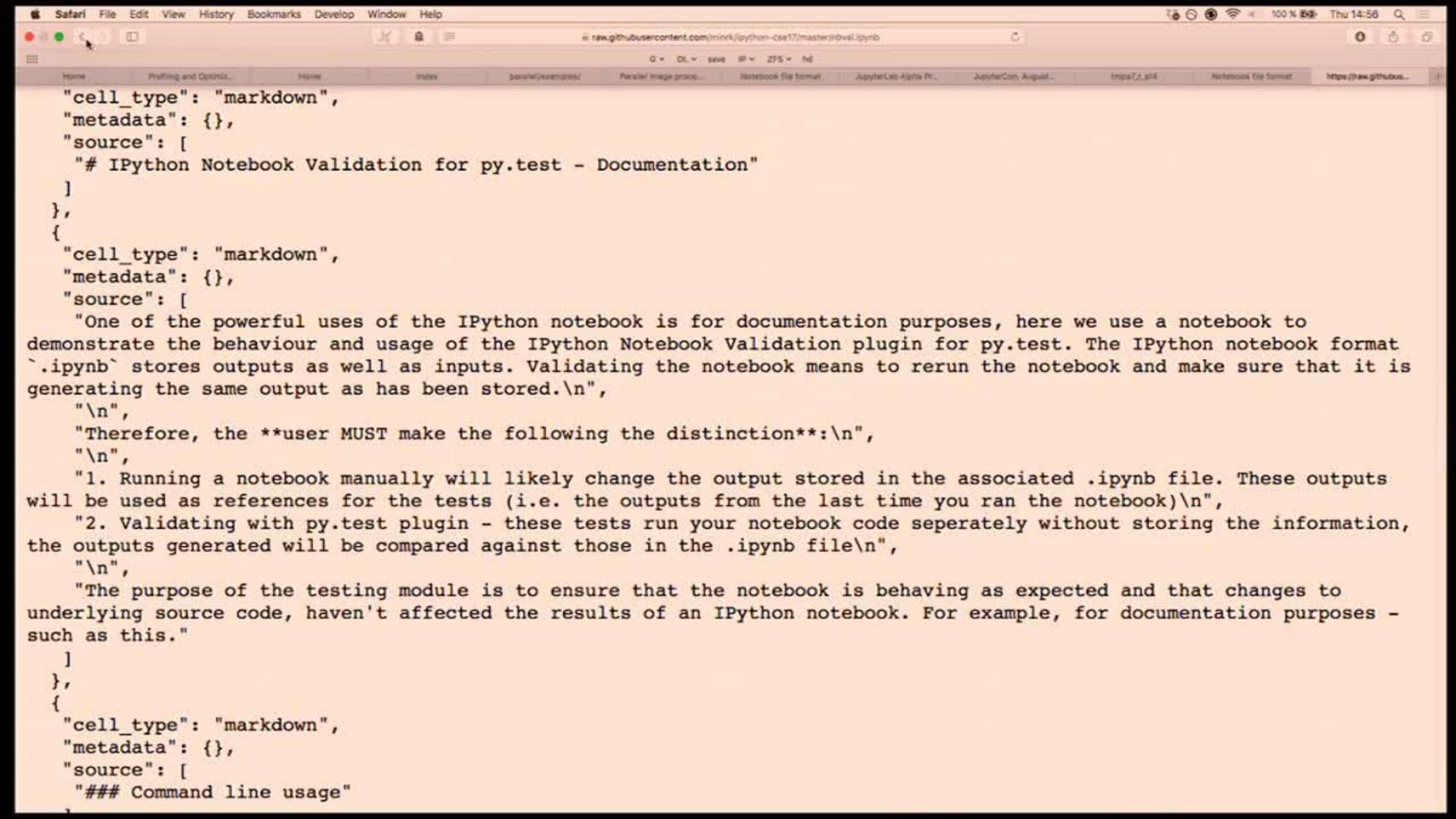
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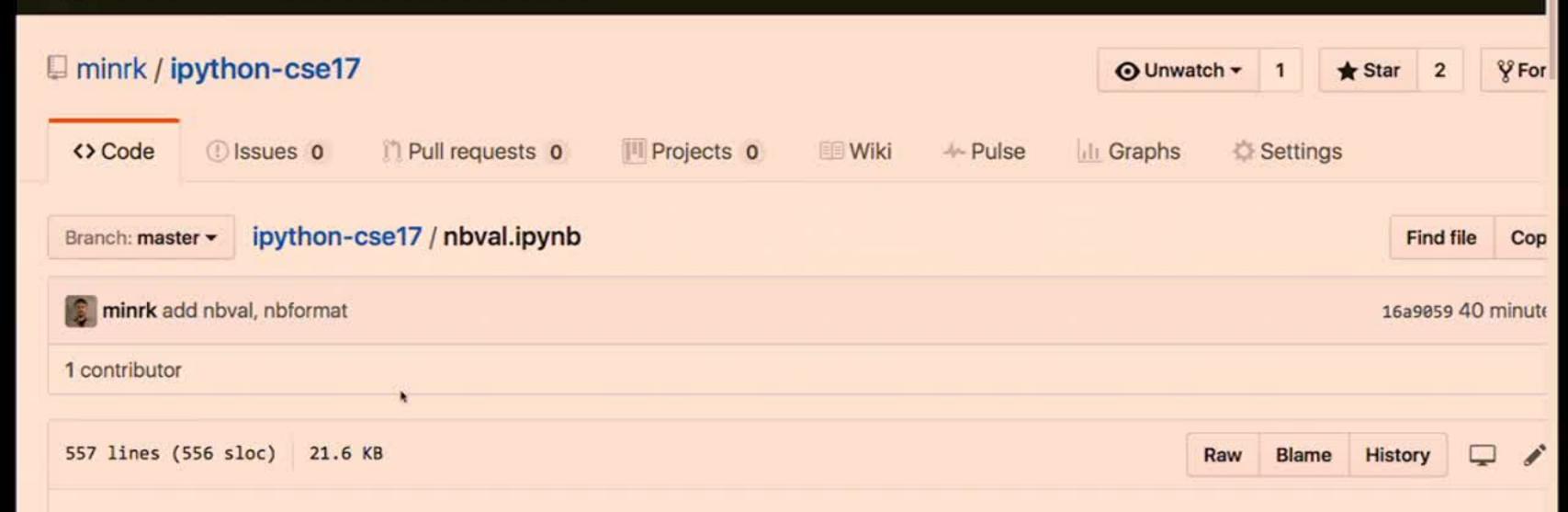
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```
"cells": [
   "cell type": "markdown",
   "metadata": {},
   "source": [
   "# IPython Notebook Validation for py.test - Documentation"
   "cell type": "markdown",
  "metadata": {},
   "source": [
    "One of the powerful uses of the IPython notebook is for documentation purposes, here we use a notebook to demonstrate the behaviour and usage of the
IPython Notebook Validation plugin for py.test. The IPython notebook format `.ipynb` stores outputs as well as inputs. Validating the notebook means to
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    "\n",
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    "\n",
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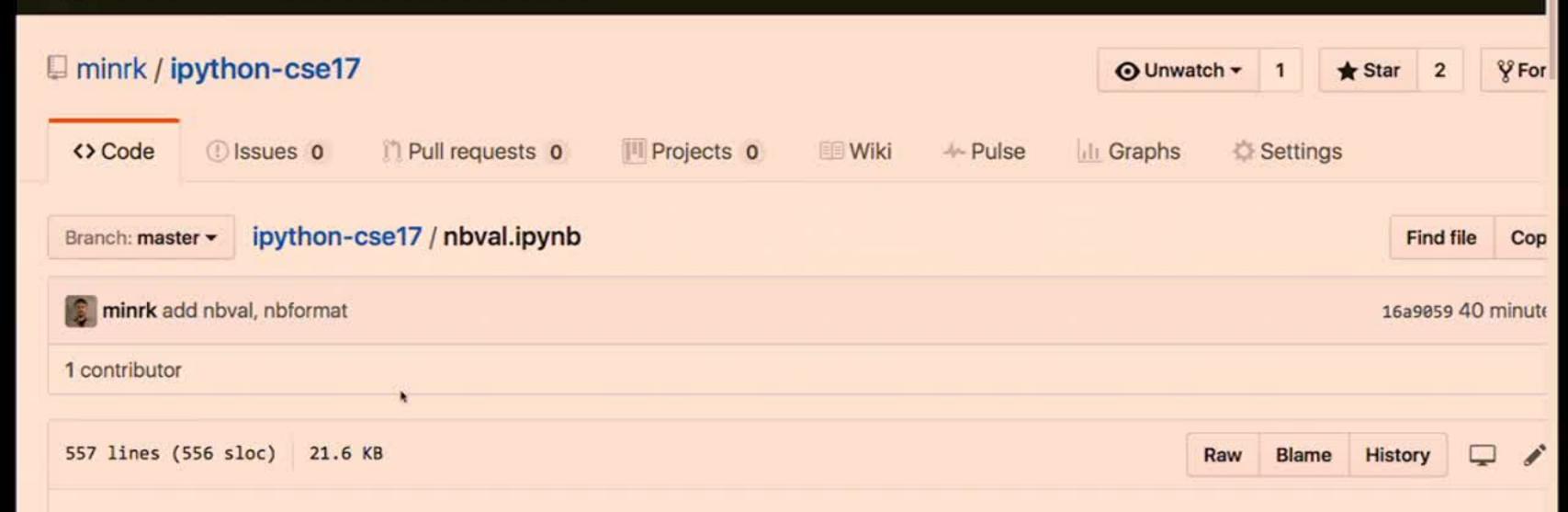




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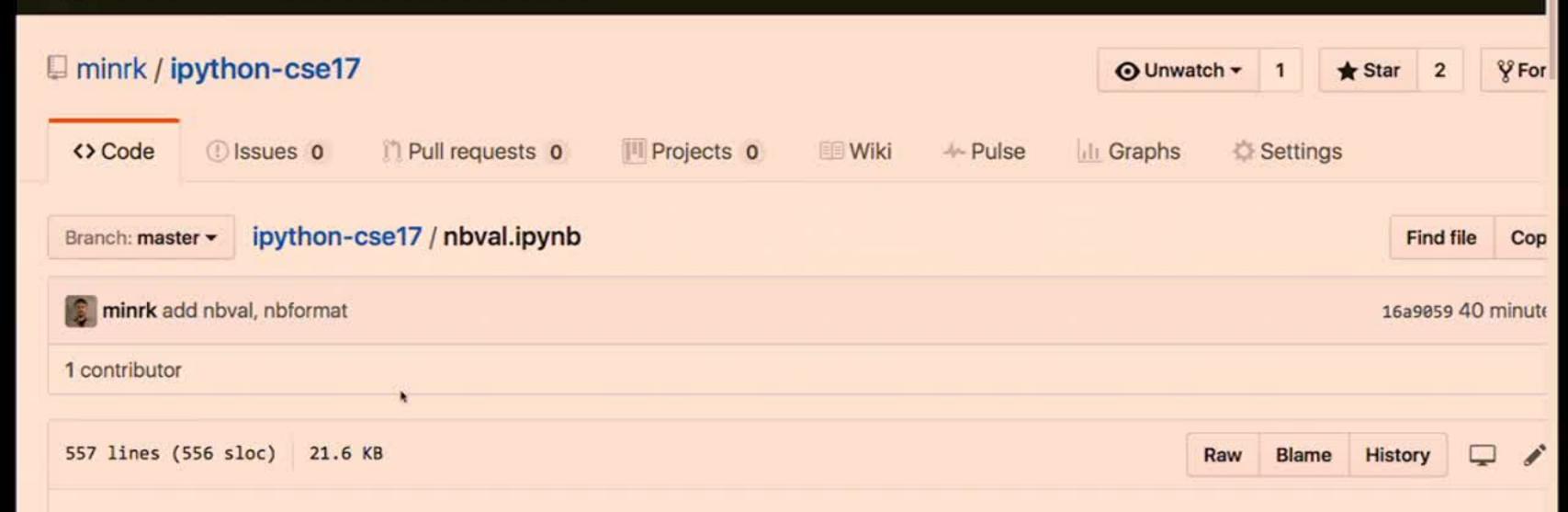
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One of the powerful uses of the IPython notebook is for documentation purposes, here we use a notebook to demonstrate the behaviour and usage of the IPython Notebook Validation plugin for py.test. The IPython notebook format .ipynb stores outputs as well as inputs. Validating the notebook means to rerun the notebook and make sure that it is generating the same output as has been stored.

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generated will be compared against those in the apynome

The purpose of the testing module is to ensure that the notebook is behaving as expected and that changes to underlying source code, haven't affected the results of an IPython notebook. For example, for documentation purposes - such as this.

# Command line usage

The py.test program doesn't usually collect notebooks for testing; by passing the --nbval flag at the command line, the IPython Notebook Validation plugin will collect and test notebook cells, comparing their outputs with those saved in the file.

```
$ py.test --nbval my notebook.ipynb
```

There is also an option --nbval-lax, which collects notebooks and runs them, failing if there is an error. This mode does not check the output of cells unless they are marked with a special #NBVAL\_CHECK\_OUTPUT comment.

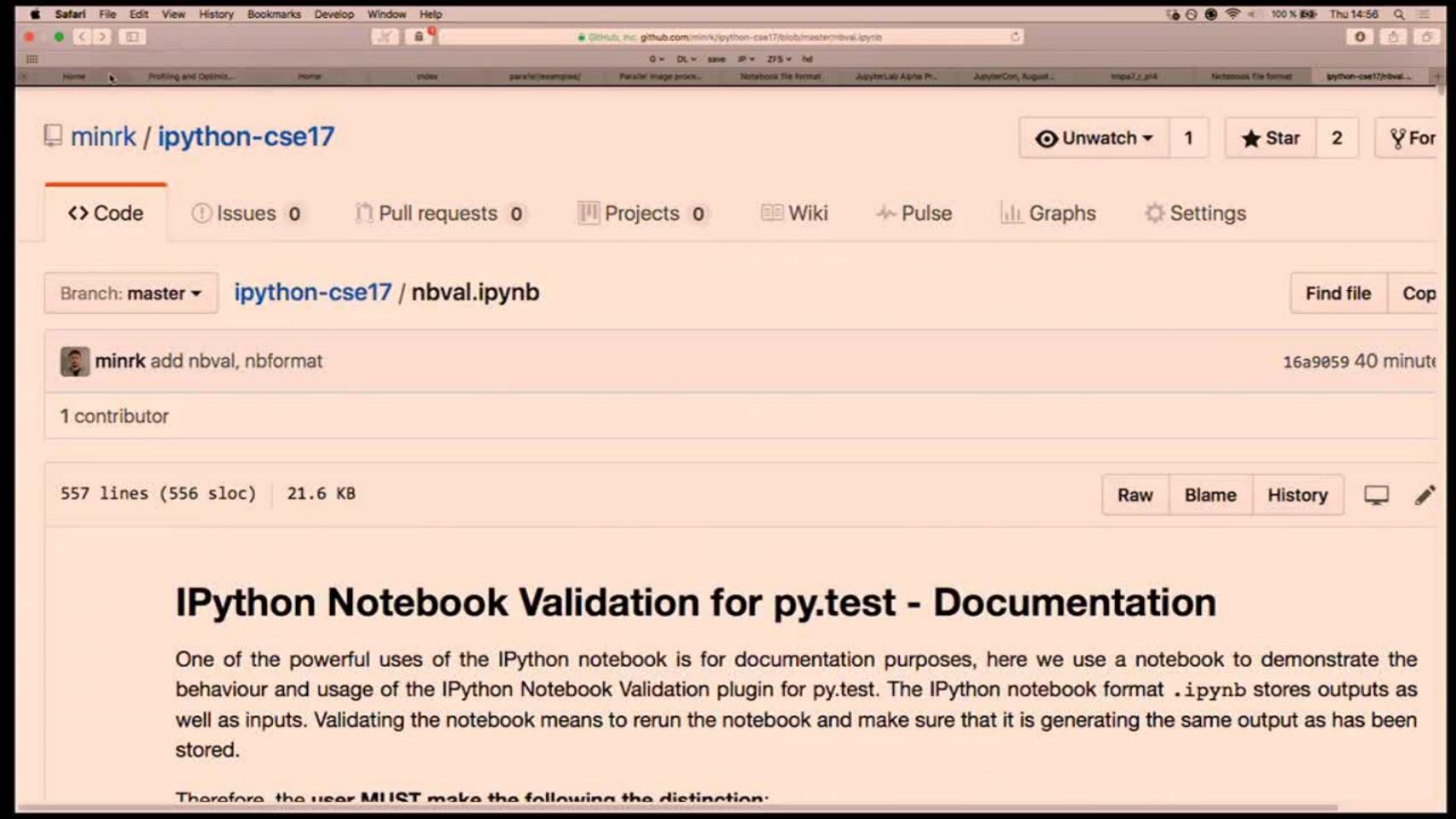
```
$ py.test --nbval-lax my notebook.ipynb
```

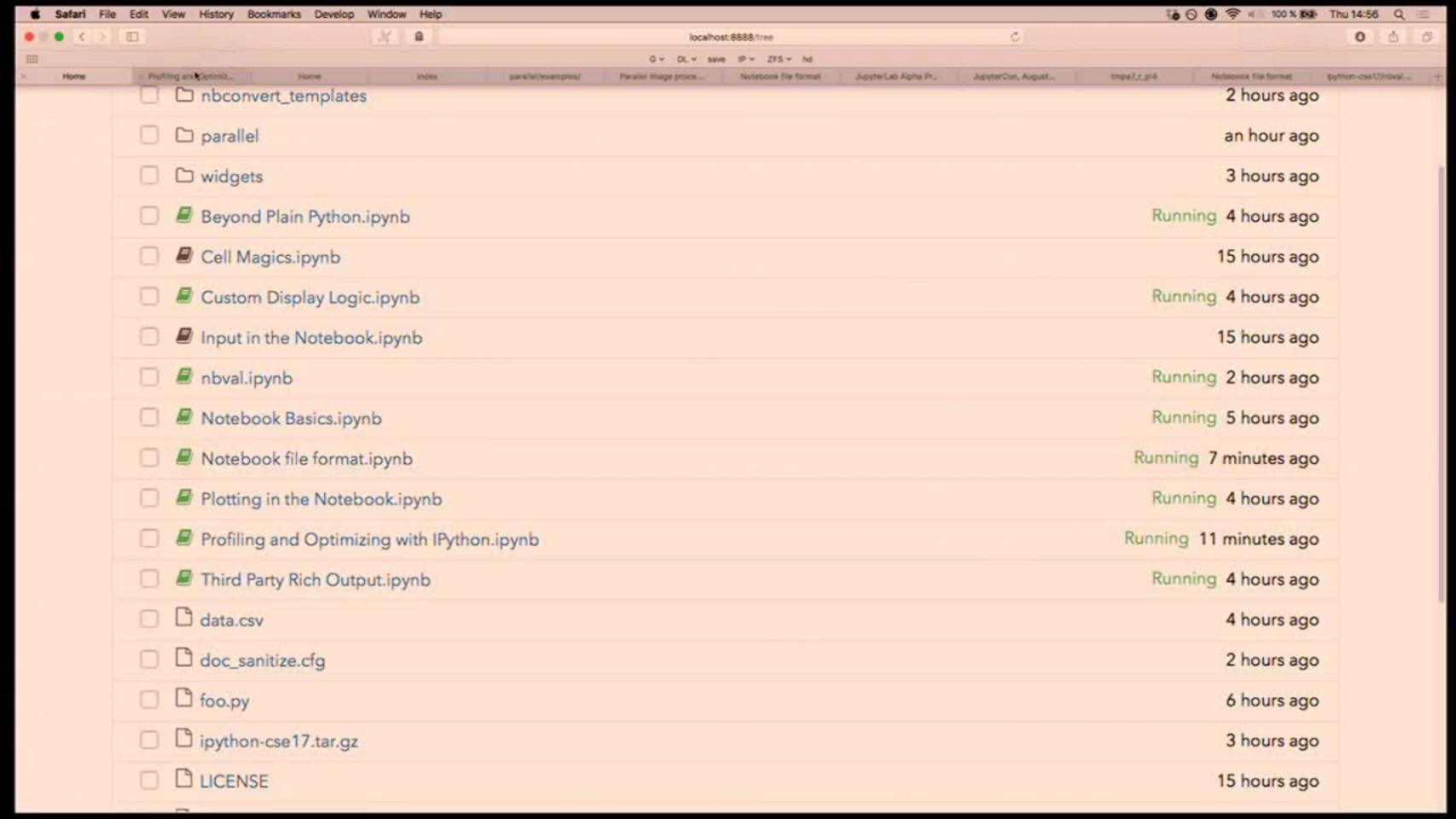
# **REGEX Output sanitizing**

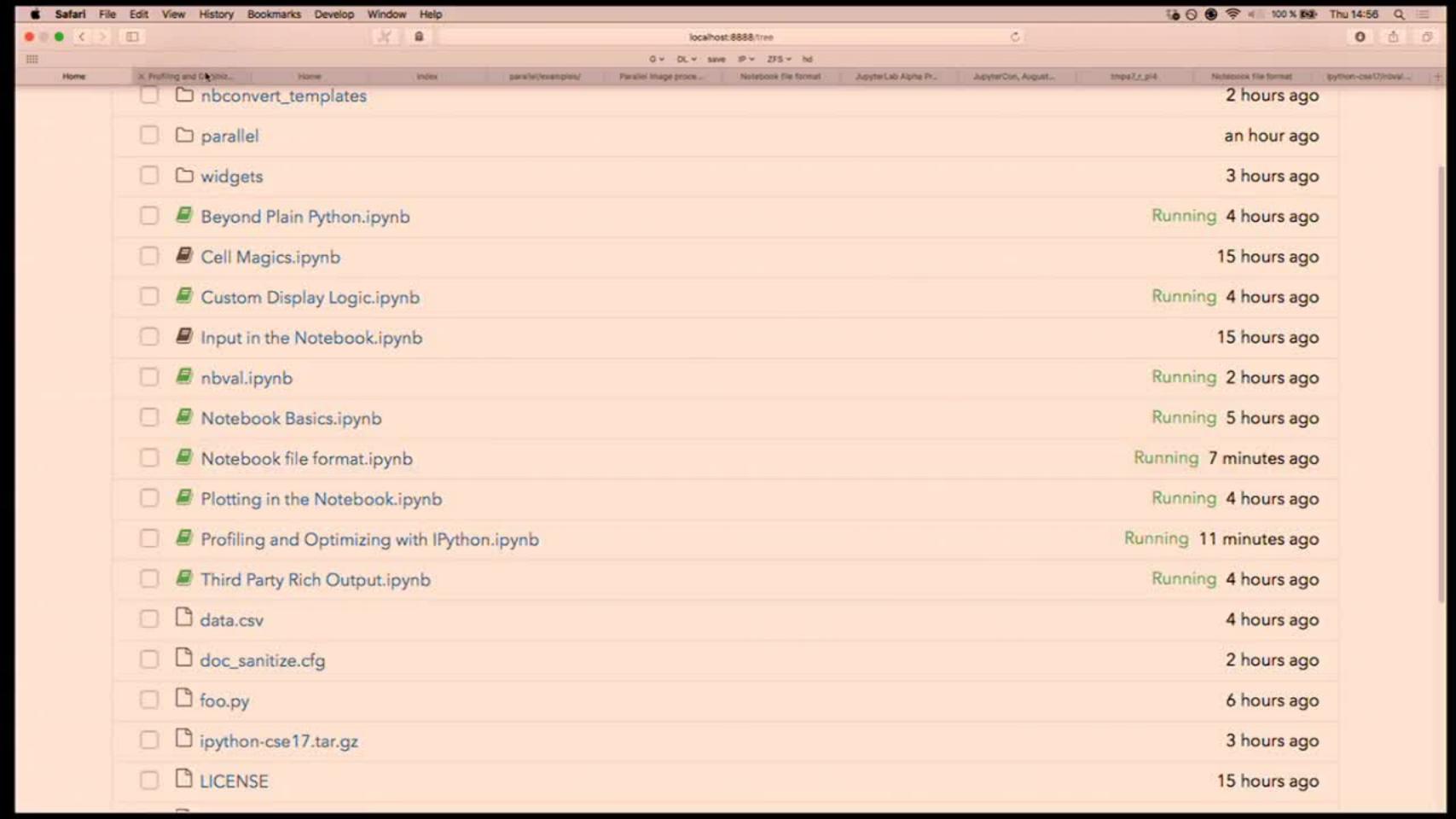
Since all output is captured by the IPython notebook, some pesky messages and prompts (with time-stamped messages, for example) may fail tests always, which might be expected. The plugin allows the user to specify a sanitizing file at the command prompt using the following flag:

```
$ py.test --nbval my_notebook.ipynb --sanitize-with my_sanitize_file
```

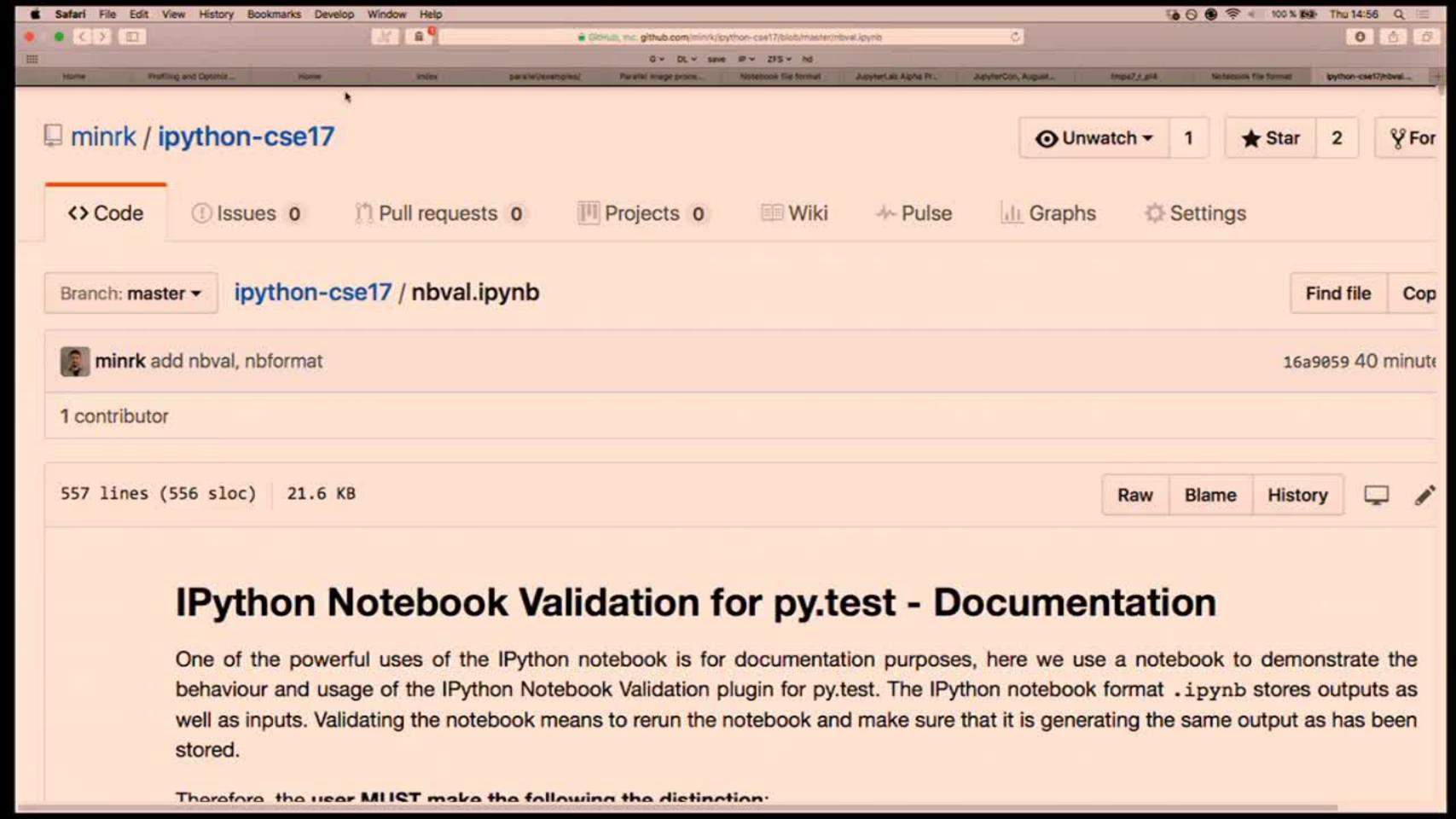
This sanitize file contains a number of REGEX replacements. It is recommended, when removing output for the tests, that you replace the removed output with some sort of marker, this helps with debugging. The following file is written to the folder of this notebook and can be used to santize its outputs:











FAQ



# nbviewer

A simple way to share Jupyter Notebooks

URL | GitHub username | GitHub username/repo | Gist ID

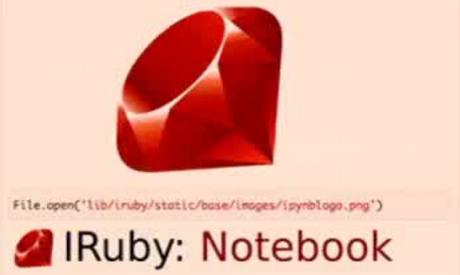
Go!

# **Programming Languages**

**IPython** 







Julia





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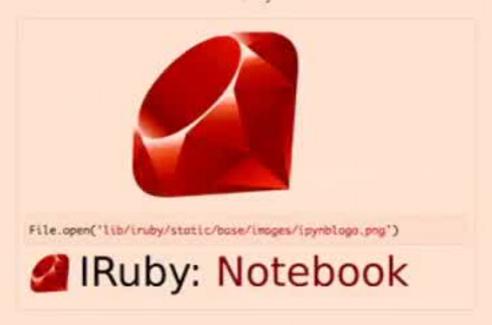
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#### **IPython**



### **IRuby**



#### Julia



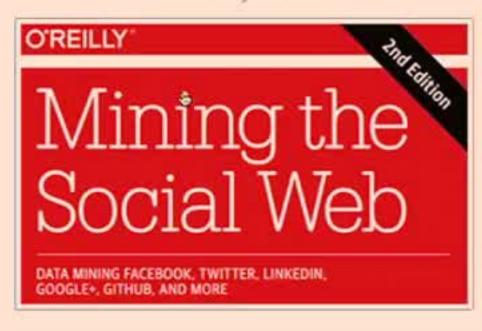


#### Python for Signal Processing

# Python for Signal Processing

### **Books**

O'Reilly Book



#### Probabilistic Programming



#### Misc

#### Data Visualization with Lightning



#### Interactive data visualization with Bokeh



#### Interactive plots with Plotly



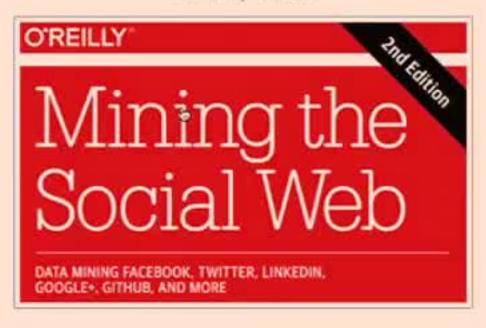


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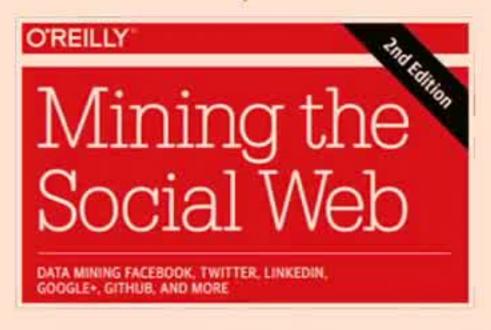


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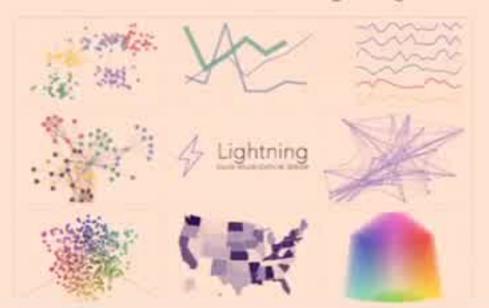


Probabilistic Programming



## Misc

Data Visualization with Lightning



Interactive data visualization with Bokeh



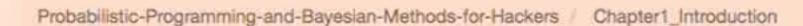
Interactive plots with Plotly











# **Probabilistic Programming**

# and Bayesian Methods for Hackers

Version 0.1

Original content created by Cam Davidson-Pilon

Ported to Python 3 and PyMC3 by Max Margenot (@clean utensils) and Thomas Wiecki (@twiecki) at Quantopian (@quantopian)

Welcome to Bayesian Methods for Hackers. The full Github repository is available at github/Probabilistic-Programming-and-Bayesian-Methods-for-Hackers. The other chapters can be found on the project's homepage. We hope you enjoy the book, and we encourage any contributions!

# Chapter 1

# The Philosophy of Bayesian Inference

You are a skilled programmer, but bugs still slip into your code. After a particularly difficult implementation of an algorithm, you decide to test your code on a trivial example. It passes. You test the code on a harder problem. It passes once again. And it passes the next, even more difficult, test too! You are starting to believe that there may be no bugs in this code...









Probabilistic-Programming-and-Bayesian-Methods-for-Hackers Chapter1\_Introduction

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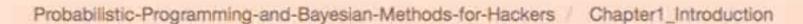
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# Chapter 1









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# Chapter 1

If you think this way, then congratulations, you already are thinking Bayesian! Bayesian inference is simply updating your beliefs after considering new evidence. A Bayesian can rarely be certain about a result, but he or she can be very confident. Just like in the example above, we can never be 100% sure that our code is bug-free unless we test it on every possible problem; something rarely possible in practice. Instead, we can test it on a large number of problems, and if it succeeds we can feel more *confident* about our code, but still not certain. Bayesian inference works identically: we update our beliefs about an outcome; rarely can we be absolutely sure unless we rule out all other alternatives.

# The Bayesian state of mind

Bayesian inference differs from more traditional statistical inference by preserving uncertainty. At first, this sounds like a bad statistical technique. Isn't statistics all about deriving certainty from randomness? To reconcile this, we need to start thinking like Bayesians.

The Bayesian world-view interprets probability as measure of believability in an event, that is, how confident we are in an event occurring. In fact, we will see in a moment that this is the natural interpretation of probability.

For this to be clearer, we consider an alternative interpretation of probability: *Frequentist*, known as the more *classical* version of statistics, assume that probability is the long-run frequency of events (hence the bestowed title). For example, the *probability of plane accidents* under a frequentist philosophy is interpreted as the *long-term frequency of plane accidents*. This makes logical sense for many probabilities of events, but becomes more difficult to understand when events have no long-term frequency of occurrences. Consider: we often assign probabilities to outcomes of presidential elections, but the election itself only happens once! Frequentists get around this by invoking alternative realities and saying across all these realities, the frequency of

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Notice in the paragraph above, I assigned the belief (probability) measure to an *individual*, not to Nature. This is very interesting, as this definition leaves room for conflicting beliefs between individuals. Again, this is appropriate for what naturally occurs: different individuals have different beliefs of events occurring, because they possess different *information* about the world. The existence of different beliefs does not imply that anyone is wrong. Consider the following examples demonstrating the relationship between individual beliefs and probabilities:

- I flip a coin, and we both guess the result. We would both agree, assuming the coin is
  fair, that the probability of Heads is 1/2. Assume, then, that I peek at the coin. Now I
  know for certain what the result is: I assign probability 1.0 to either Heads or Tails
  (whichever it is). Now what is your belief that the coin is Heads? My knowledge of the
  outcome has not changed the coin's results. Thus we assign different probabilities to
  the result.
- Your code either has a bug in it or not, but we do not know for certain which is true, though we have a belief about the presence or absence of a bug.
- A medical patient is exhibiting symptoms x, y and z. There are a number of diseases
  that could be causing all of them, but only a single disease is present. A doctor has
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This philosophy of treating beliefs as probability is natural to humans. We employ it constantly as we interact with the world and only see partial truths, but gather evidence to form beliefs.

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To align ourselves with traditional probability notation, we denote our belief about event A as P(A). We call this quantity the *prior probability*.

John Maynard Keynes, a great economist and thinker, said "When the facts change, I change my mind. What do you do, sir?" This quote reflects the way a Bayesian updates his or her beliefs after seeing evidence. Even — especially — if the evidence is counter to what was initially believed, the evidence cannot be ignored. We denote our updated belief as P(A|X), interpreted

It's clear that in each example we did not completely discard the prior belief after seeing new evidence X, but we re-weighted the prior to incorporate the new evidence (i.e. we put more weight, or confidence, on some beliefs versus others).

By introducing prior uncertainty about events, we are already admitting that any guess we make is potentially very wrong. After observing data, evidence, or other information, we update our beliefs, and our guess becomes less wrong. This is the alternative side of the prediction coin, where typically we try to be more right.

# **Bayesian Inference in Practice**

If frequentist and Bayesian inference were programming functions, with inputs being statistical problems, then the two would be different in what they return to the user. The frequentist inference function would return a number, representing an estimate (typically a summary statistic like the sample average etc.), whereas the Bayesian function would return probabilities.

For example, in our debugging problem above, calling the frequentist function with the argument "My code passed all X tests; is my code bug-free?" would return a YES. On the other hand, asking our Bayesian function "Often my code has bugs. My code passed all X tests; is my code bug-free?" would return something very different; probabilities of YES and NO. The function might return:

YES, with probability 0.8; NO, with probability 0.2

This is very different from the answer the frequentist function returned. Notice that the Bayesian function accepted an additional argument: "Often my code has bugs". This parameter is the prior. By including the prior parameter, we are telling the Bayesian function to include our belief about

triis beliet.

Denote N as the number of instances of evidence we possess. As we gather an *infinite* amount of evidence, say as  $N \to \infty$ , our Bayesian results (often) align with frequentist results. Hence for large N, statistical inference is more or less objective. On the other hand, for small N, inference is much more *unstable*: frequentist estimates have more variance and larger confidence intervals. This is where Bayesian analysis excels. By introducing a prior, and returning probabilities (instead of a scalar estimate), we *preserve the uncertainty* that reflects the instability of statistical inference of a small N dataset.

One may think that for large N, one can be indifferent between the two techniques since they offer similar inference, and might lean towards the computationally-simpler, frequentist methods. An individual in this position should consider the following quote by Andrew Gelman (2005)[1], before making such a decision:

Sample sizes are never large. If N is too small to get a sufficiently-precise estimate, you need to get more data (or make more assumptions). But once N is "large enough," you can start subdividing the data to learn more (for example, in a public opinion poll, once you have a good estimate for the entire country, you can estimate among men and women, northerners and southerners, different age groups, etc.). N is never enough because if it were "enough" you'd already be on to the next problem for which you need more data.

# Are frequentist methods incorrect then?

No.

Frequentist methods are still useful or state-of-the-art in many areas. Tools such as least squares

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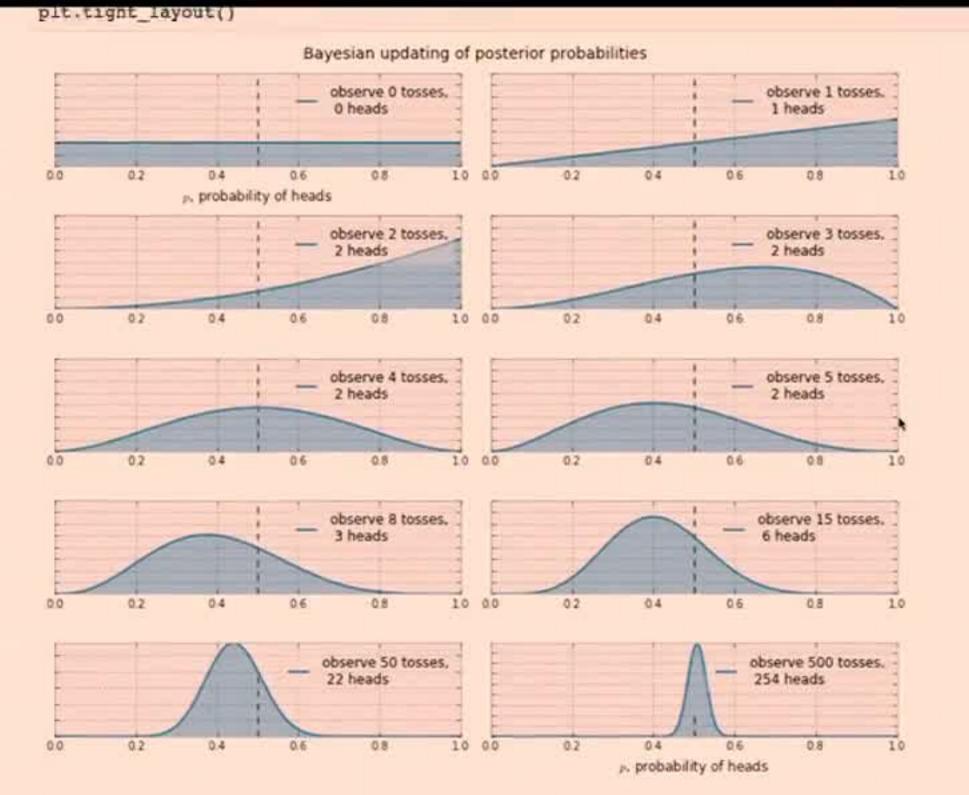
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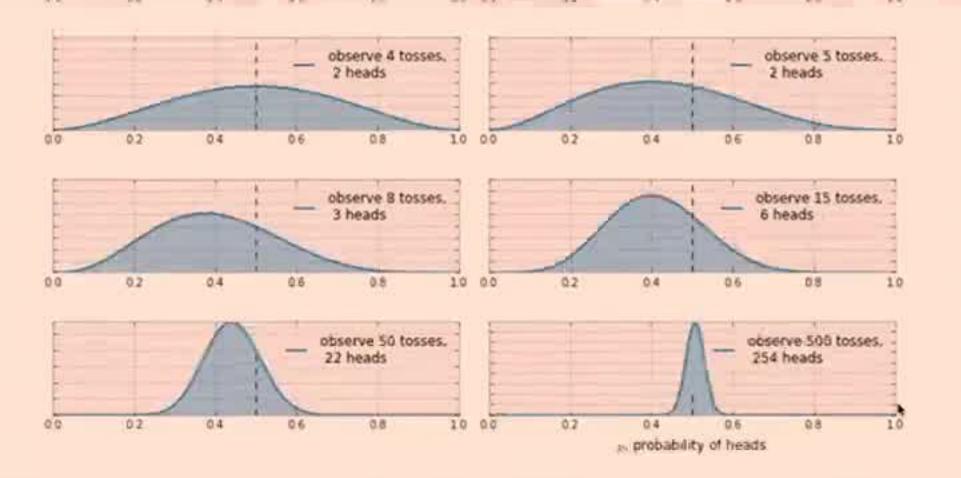
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The posterior probabilities are represented by the curves, and our uncertainty is proportional to the width of the curve. As the plot above shows, as we start to observe data our posterior probabilities start to shift and move around. Eventually, as we observe more and more data (coin-flips), our probabilities will tighten closer and closer around the true value of p=0.5 (marked by



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Notice that the plots are not always peaked at 0.5. There is no reason it should be: recall we assumed we did not have a prior opinion of what p is. In fact, if we observe quite extreme data, say 8 flips and only 1 observed heads, our distribution would look very biased away from lumping around 0.5 (with no prior opinion, how confident would you feel betting on a fair coin after observing 8 tails and 1 head). As more data accumulates, we would see more and more probability being assigned at p=0.5, though never all of it.

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The next example is a simple demonstration of the mathematics of Bayesian inference.

# Example: Bug, or just sweet, unintended feature?

Let A denote the event that our code has **no bugs** in it. Let X denote the event that the code passes all debugging tests. For now, we will leave the prior probability of no bugs as a variable, i.e. P(A) = p.

We are interested in P(A|X), i.e. the probability of no bugs, given our debugging tests X. To use the formula above, we need to compute some quantities.

What is P(X|A), i.e., the probability that the code passes X tests given there are no bugs? Well, it is equal to 1, for a code with no bugs will pass all tests.

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P(X) is a little bit trickier: The event X can be divided into two possibilities, event X occurring even though our code *indeed has* bugs (denoted  $\sim A$ , spoken not A), or event X without bugs (A). P(X) can be represented as:

$$P(X) = P(X \text{ and } A) + P(X \text{ and } \sim A)$$
 (4)

(5)

$$= P(X|A)P(A) + P(X| \sim A)P(\sim A) \tag{6}$$

(7)

$$= P(X|A)p + P(X| \sim A)(1-p)$$
 (8)

Let A denote the event that our code has **no bugs** in it. Let X denote the event that the code passes all debugging tests. For now, we will leave the prior probability of no bugs as a variable, i.e. P(A) = p.

We are interested in P(A|X), i.e. the probability of no bugs, given our debugging tests X. To use the formula above, we need to compute some quantities.

What is P(X|A), i.e., the probability that the code passes X tests given there are no bugs? Well, it is equal to 1, for a code with no bugs will pass all tests.

P(X) is a little bit trickier: The event X can be divided into two possibilities, event X occurring even though our code *indeed has* bugs (denoted  $\sim A$ , spoken *not* A), or event X without bugs (A). P(X) can be represented as:

$$P(X) = P(X \text{ and } A) + P(X \text{ and } \sim A)$$
 (4)

(5)

$$= P(X|A)P(A) + P(X| \sim A)P(\sim A) \tag{6}$$

(7)

$$= P(X|A)p + P(X| \sim A)(1-p)$$
 (8)

We have already computed P(X|A) above. On the other hand,  $P(X|\sim A)$  is subjective: our code can pass tests but still have a bug in it, though the probability there is a bug present is reduced. Note this is dependent on the number of tests performed, the degree of complication in the tests, etc. Let's be conservative and assign  $P(X|\sim A)=0.5$ . Then

$$P(A|X) = \frac{1 \cdot p}{1 - p + 0.5(1 - p)} \tag{9}$$

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(10)

```
plt.plot(p, 2*p/(1+p), color="#348ABD", 1w=3)
#plt.fill_between(p, 2*p/(1+p), alpha=.5, facecolor=["#A60628"])
plt.scatter(0.2, 2*(0.2)/1.2, s=140, c="#348ABD")
plt.xlim(0, 1)
plt.ylim(0, 1)
plt.ylim(0, 1)
plt.xlabel("Prior, $P(A) = p$")
plt.ylabel("Posterior, $P(A|X)$, with $P(A) = p$")
plt.title("Are there bugs in my code?");
```

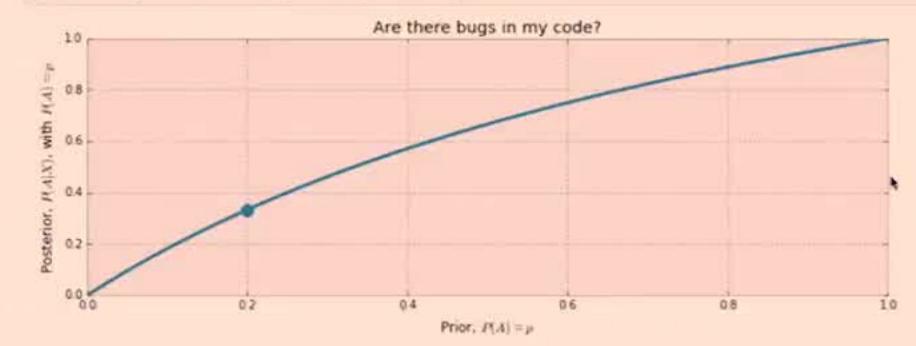


We can see the biggest gains if we observe the X tests passed when the prior probability, p, is low. Let's settle on a specific value for the prior. I'm a strong programmer (I think), so I'm going to give myself a realistic prior of 0.20, that is, there is a 20% chance that I write code bug-free. To be more realistic, this prior should be a function of how complicated and large the code is, but let's pin it at 0.20. Then my updated belief that my code is bug-free is 0.33.

Recall that the prior is a probability: p is the prior probability that there are no bugs, so 1 - p is the prior probability that there are bugs.

Similarly, our posterior is also a probability, with P(A|X) the probability there is no bug given we saw all tests pass, hence 1 - P(A|X) is the probability there is a bug given all tests passed. What does our posterior probability look like? Below is a chart of both the prior and the posterior

```
figsize(12.5, 4)
p = np.linspace(0, 1, 50)
plt.plot(p, 2*p/(1+p), color="#348ABD", lw=3)
#plt.fill_between(p, 2*p/(1+p), alpha=.5, facecolor=["#A60628"])
plt.scatter(0.2, 2*(0.2)/1.2, s=140, c="#348ABD")
plt.xlim(0, 1)
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```



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Notebooks are still at: https://github.com/minrk/ipython-cse17

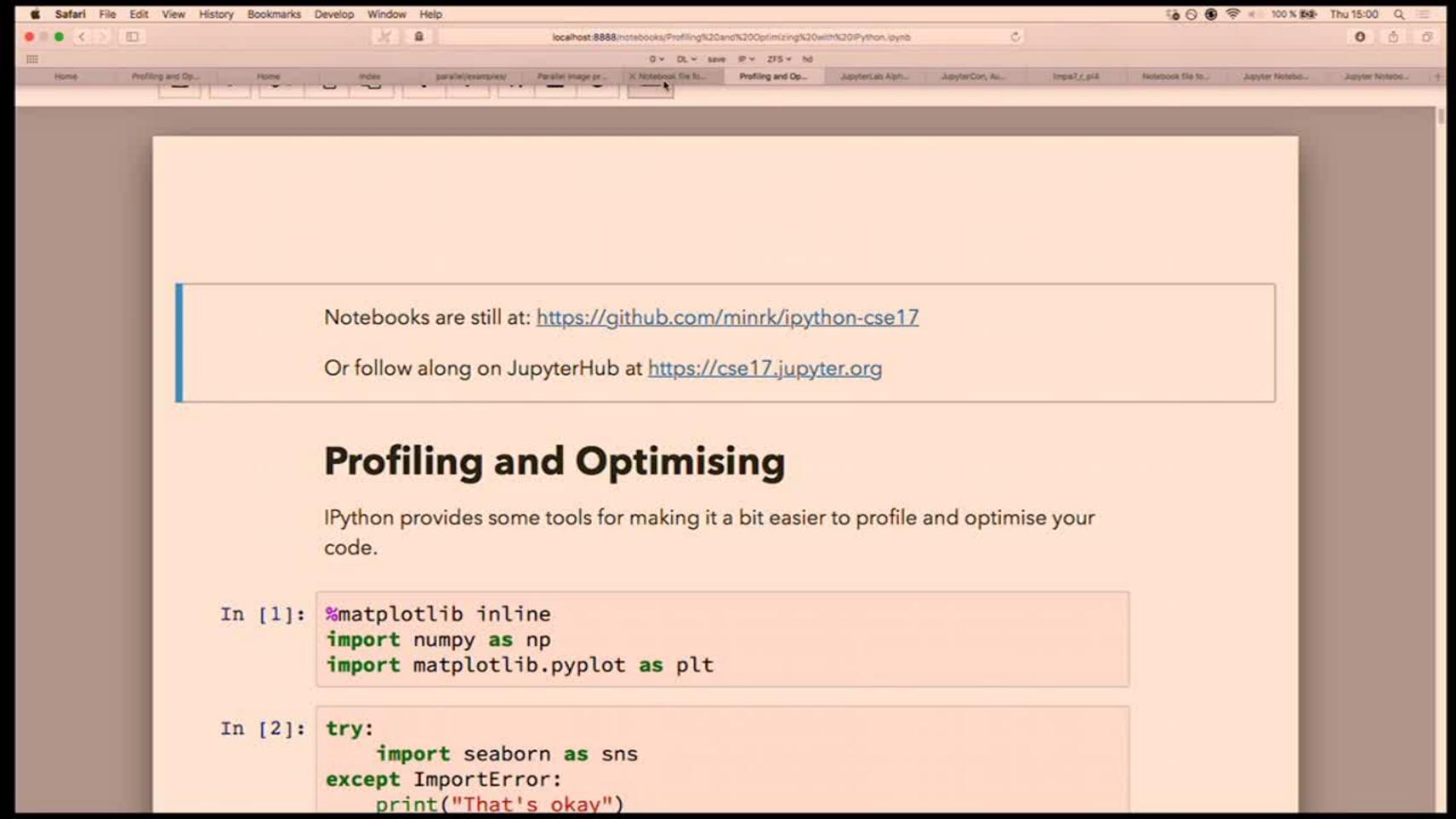
Or follow along on JupyterHub at https://cse17.jupyter.org

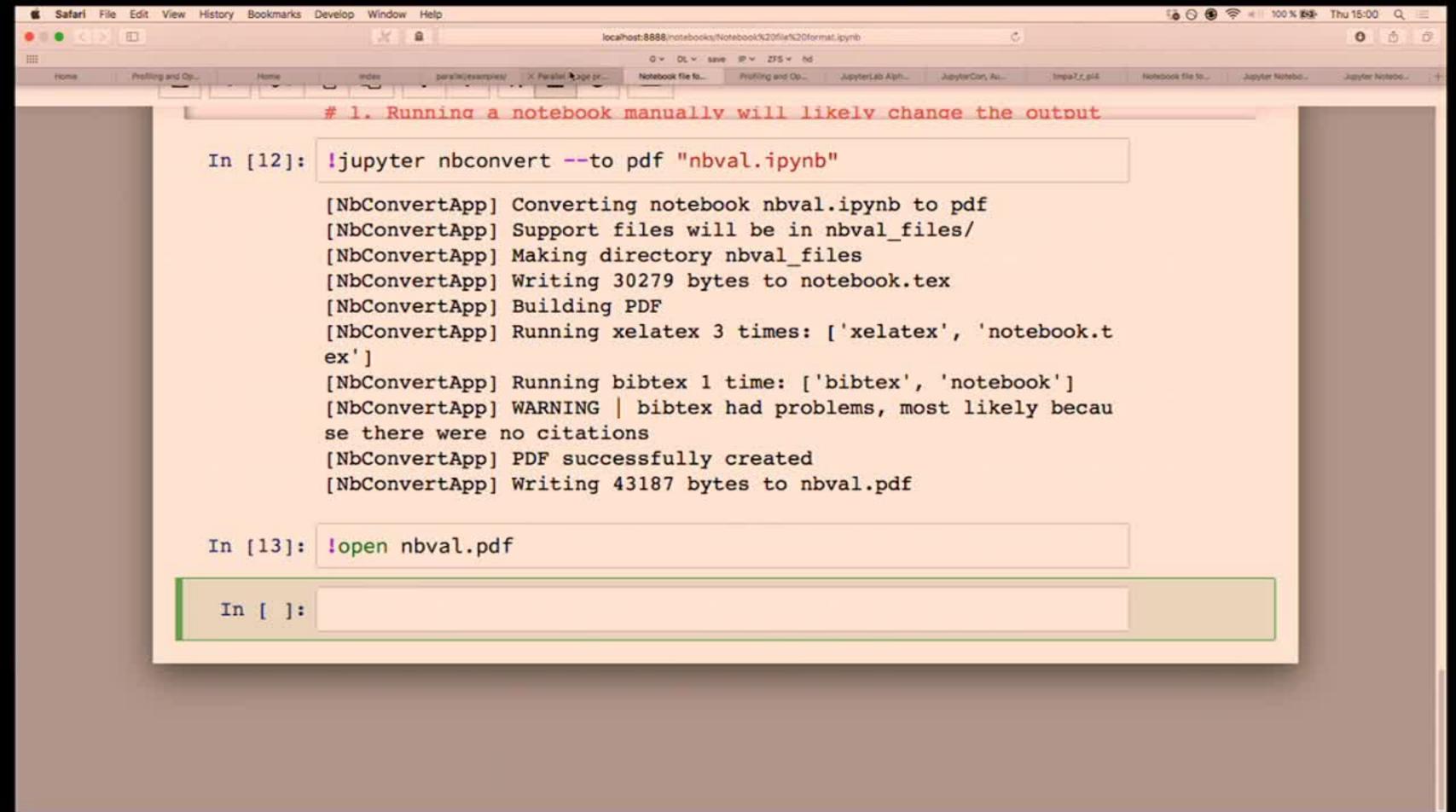
# **Profiling and Optimising**

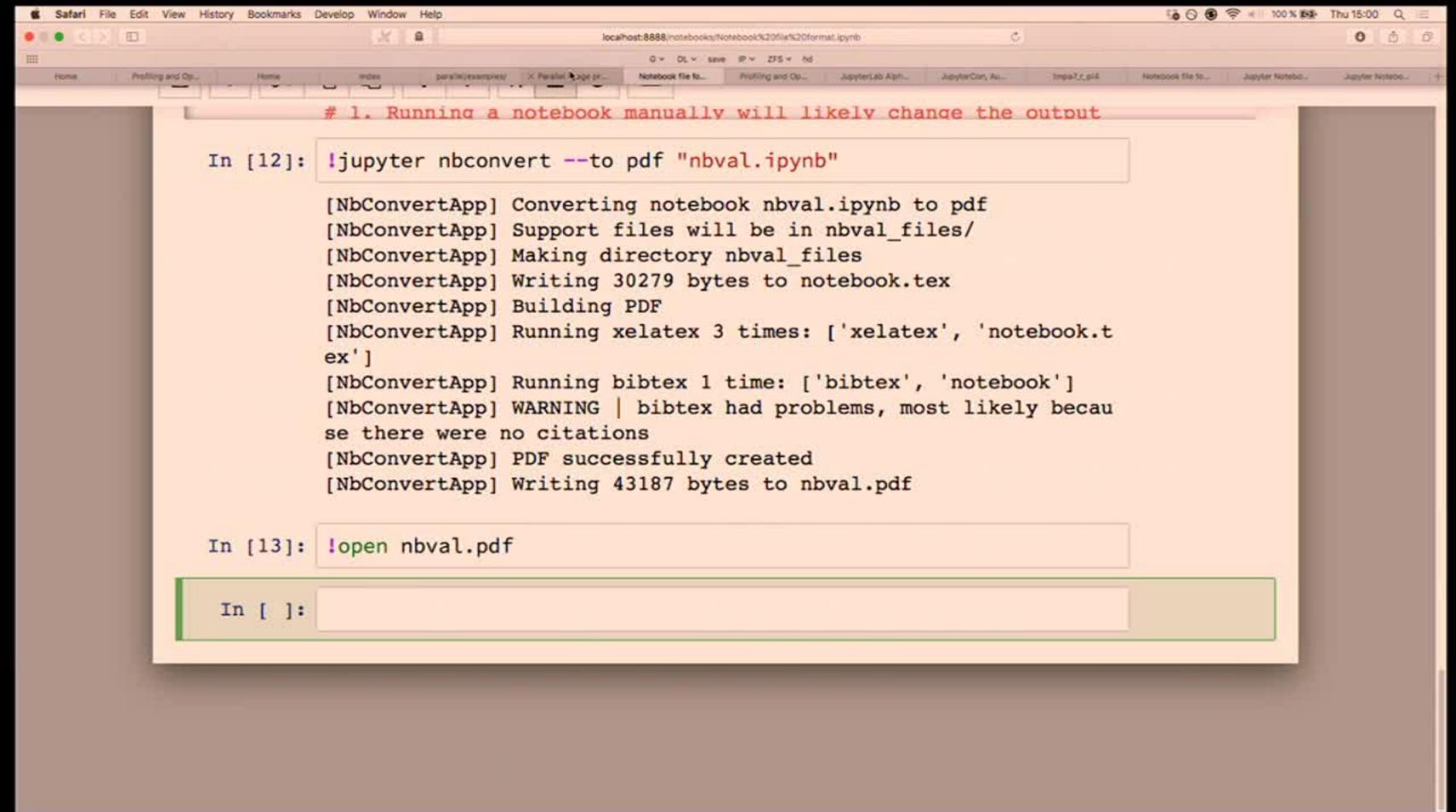
IPython provides some tools for making it a bit easier to profile and optimise your code.

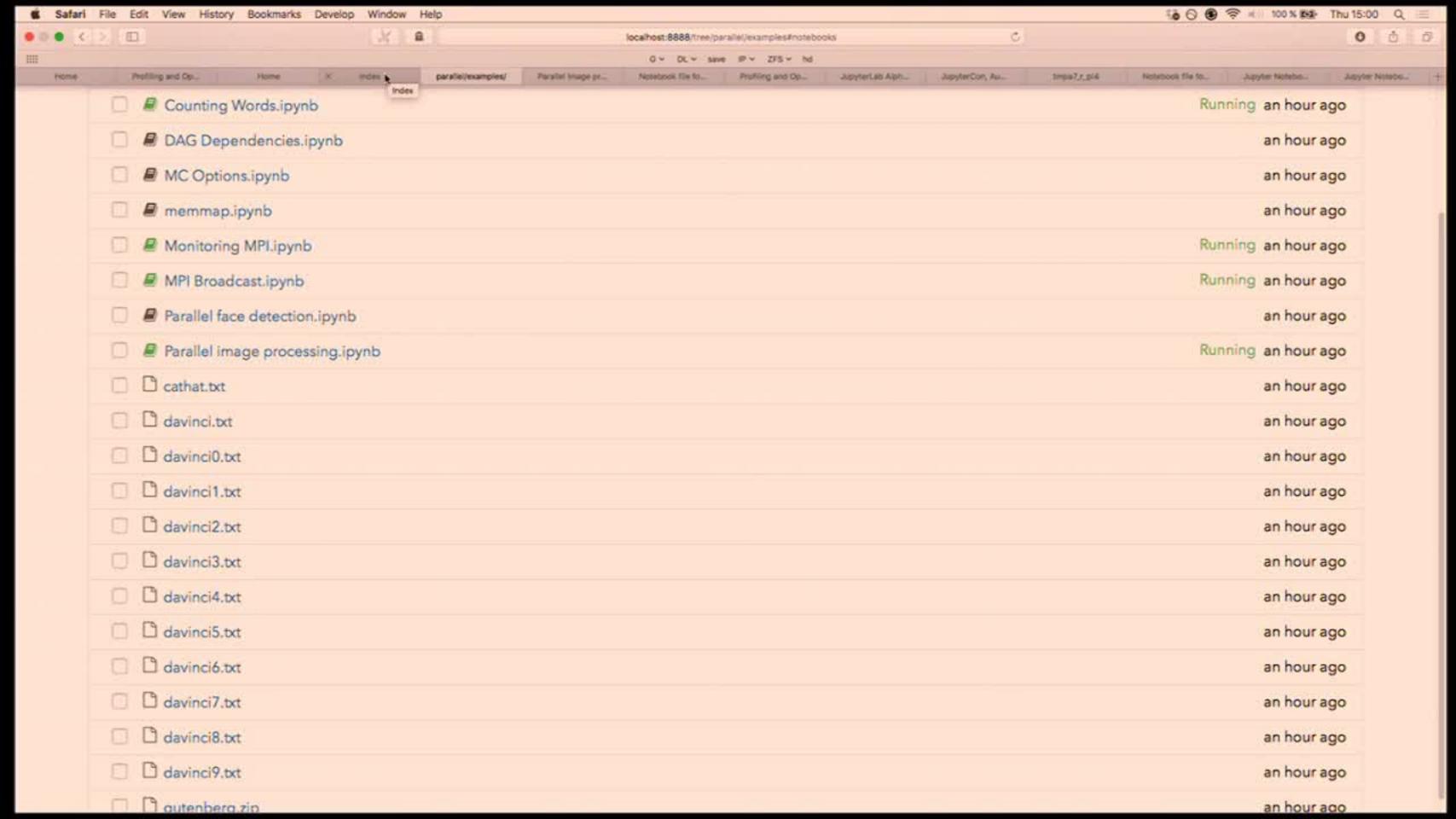
```
In [1]: %matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
```

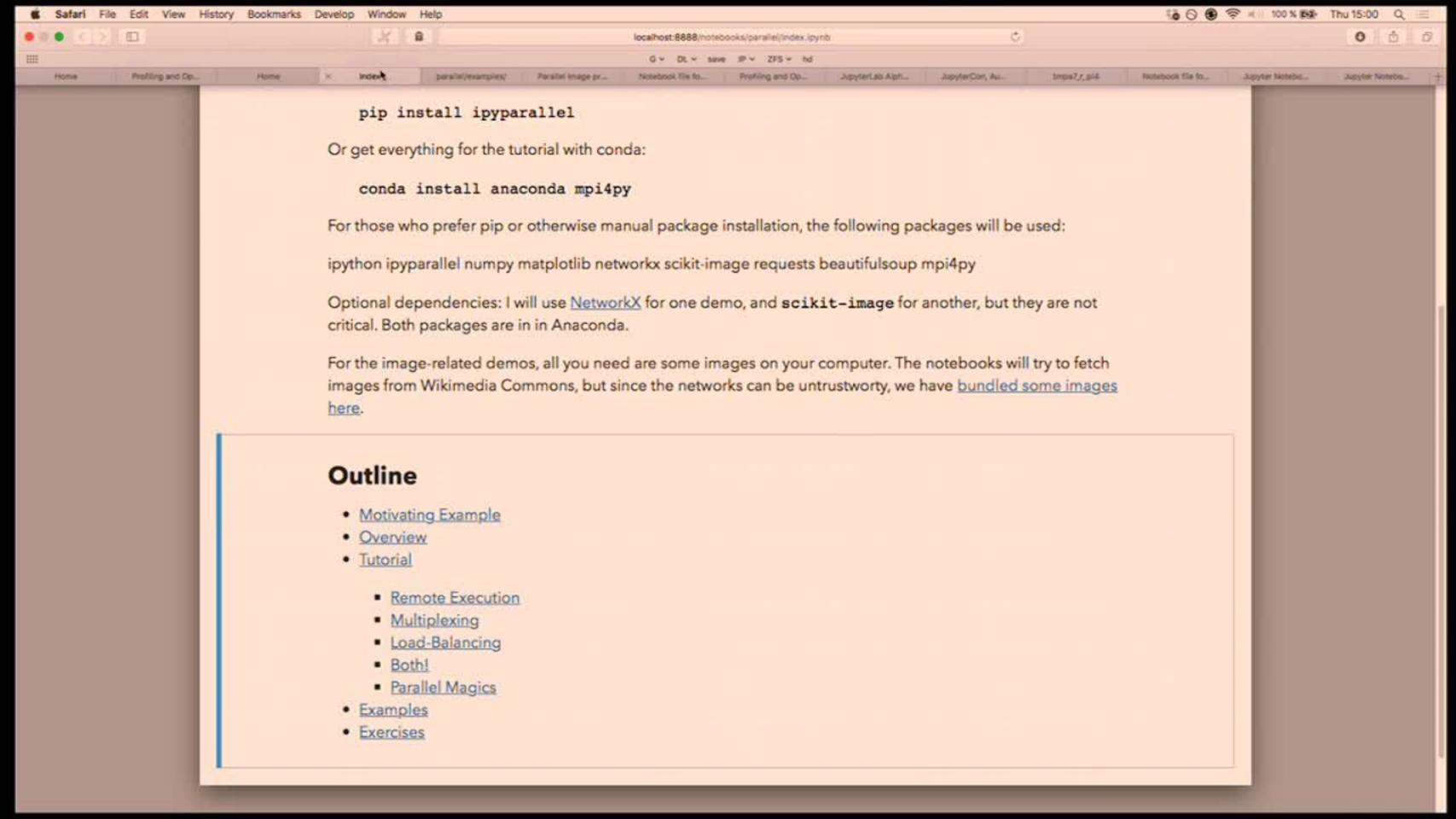
In [2]: try:
 import seaborn as sns

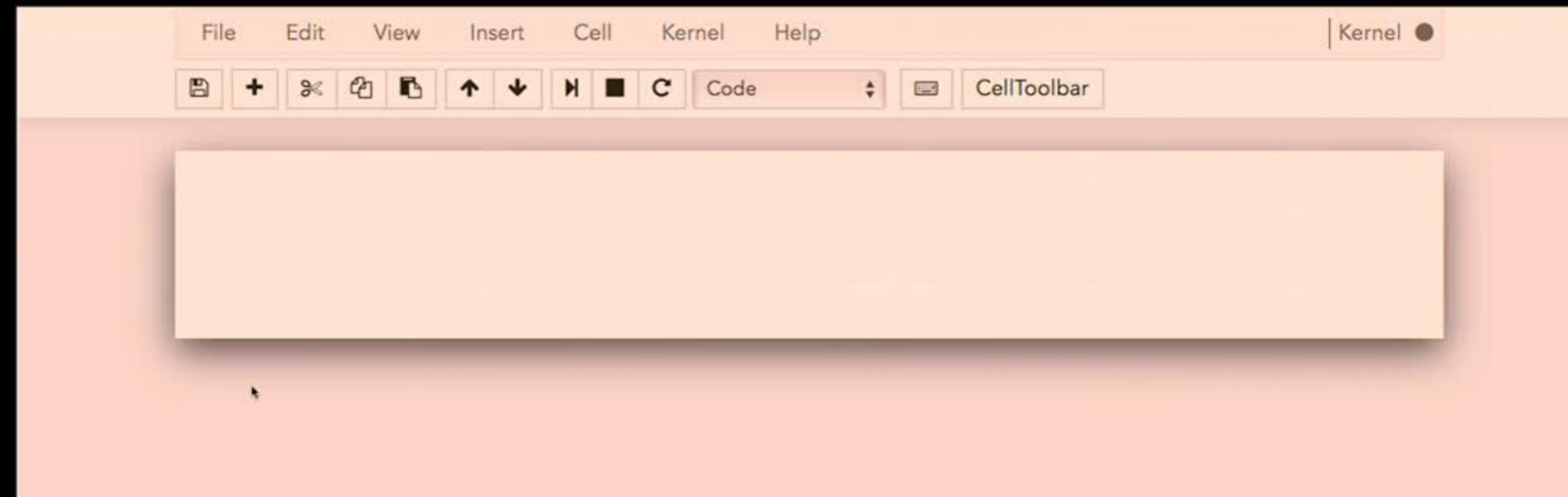












# IPython Notebook Validation for py.test - Documentation

One of the powerful uses of the IPython notebook is for documentation purposes, here we use a notebook to demonstrate the behaviour and usage of the IPython Notebook Validation plugin for py.test. The IPython notebook format .ipynb stores outputs as well as inputs. Validating the notebook means to rerun the notebook and make sure that it is generating the same output as has been stored.

Therefore, the user MUST make the following the distinction:

- Running a notebook manually will likely change the output stored in the associated .ipynb file. These outputs will be used as references for the tests (i.e. the outputs from the last time you ran the notebook)
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The purpose of the testing module is to ensure that the notebook is behaving as expected and that changes to underlying source code, haven't affected the results of an IPython notebook. For example, for documentation purposes - such as this.

# Command line usage

The py.test program doesn't usually collect notebooks for testing; by passing the --nbval flag at the command line, the IPython Notebook Validation plugin will One of the powerful uses of the IPython notebook is for documentation purposes, here we use a notebook to demonstrate the behaviour and usage of the IPython Notebook Validation plugin for py.test. The IPython notebook format .ipynb stores outputs as well as inputs. Validating the notebook means to rerun the notebook and make sure that it is generating the same output as has been stored.

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The py.test program doesn't usually collect notebooks for testing; by passing the -nbval flag at the command line, the IPython Notebook Validation plugin will
collect and test notebook cells, comparing their outputs with those saved in the file.

\$ py.test --nbval my\_notebook.ipynb

There is also an option --nbval-lax, which collects notebooks and runs them, failing if there is an error. This mode does not check the output of cells unless they are marked with a special #NBVAL\_CHECK\_OUTPUT comment.

\$ py.test --nbval-lax my\_notebook.ipynb

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\$ py.test --nbval-lax my notebook.ipynb

# **REGEX Output sanitizing**

Since all output is captured by the IPython notebook, some pesky messages and prompts (with time-stamped messages, for example) may fail tests always, which



The first replacement finds dates in the given format replaces them with the label 'DATE-STAMP', likewise for strings that look like time. These will prevent the tests from failing due to time differences.

### Validate this notebook

You can validate this notebook yourself, as shown below; the outputs that you see here are stored in the ipynb file. If your system produces different outputs, the testing process will fail. Just use the following commands:

\$ cd /path/to/this/notebook
\$ py.test --nbval nbval.ipynb --sanitize-with doc\_saniti
ze.cfg

# **Examples of plugin behaviour**

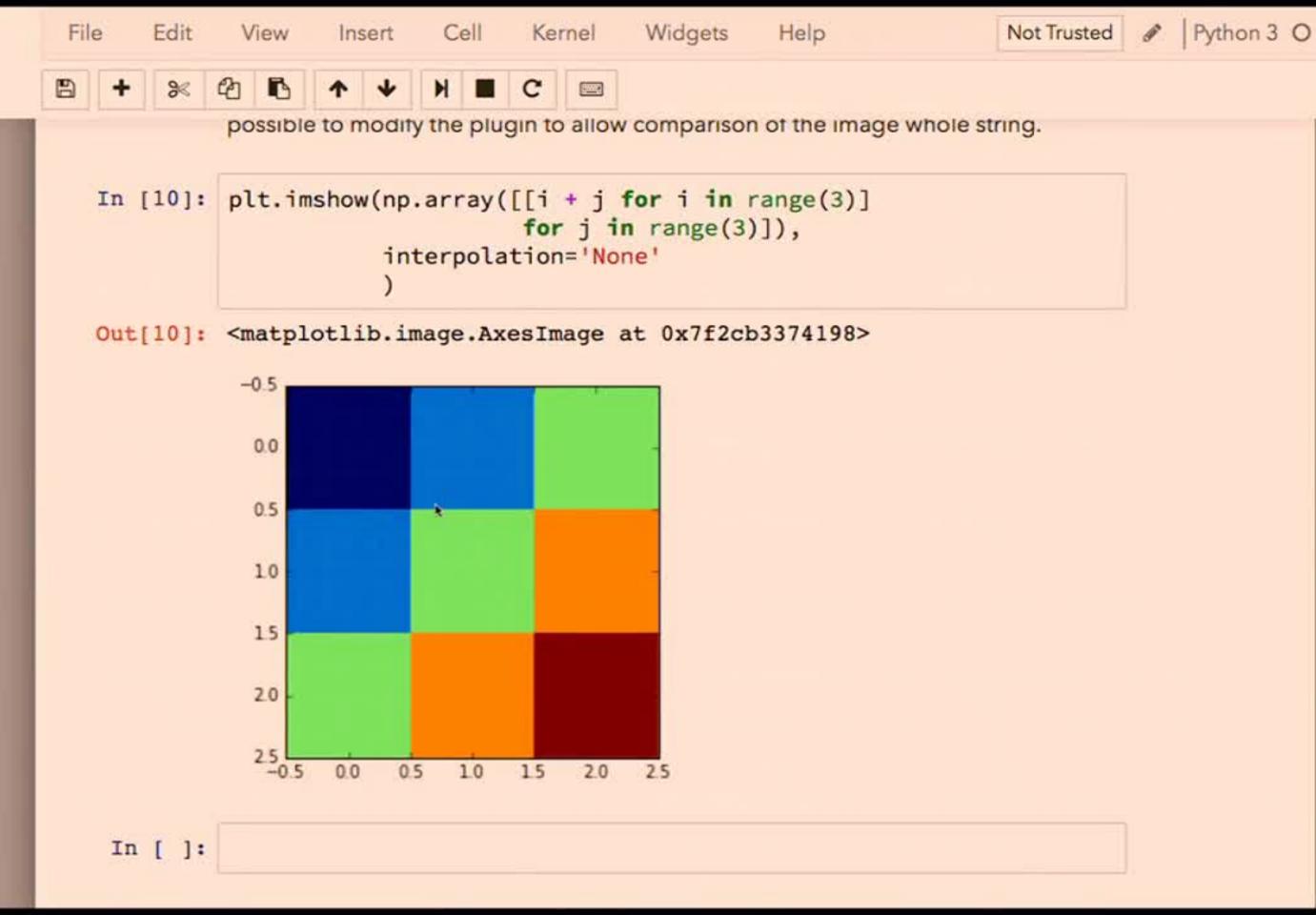
The following examples demonstrate how the plugin behaves during testing. Test this notebook yourself to see the validation in action!

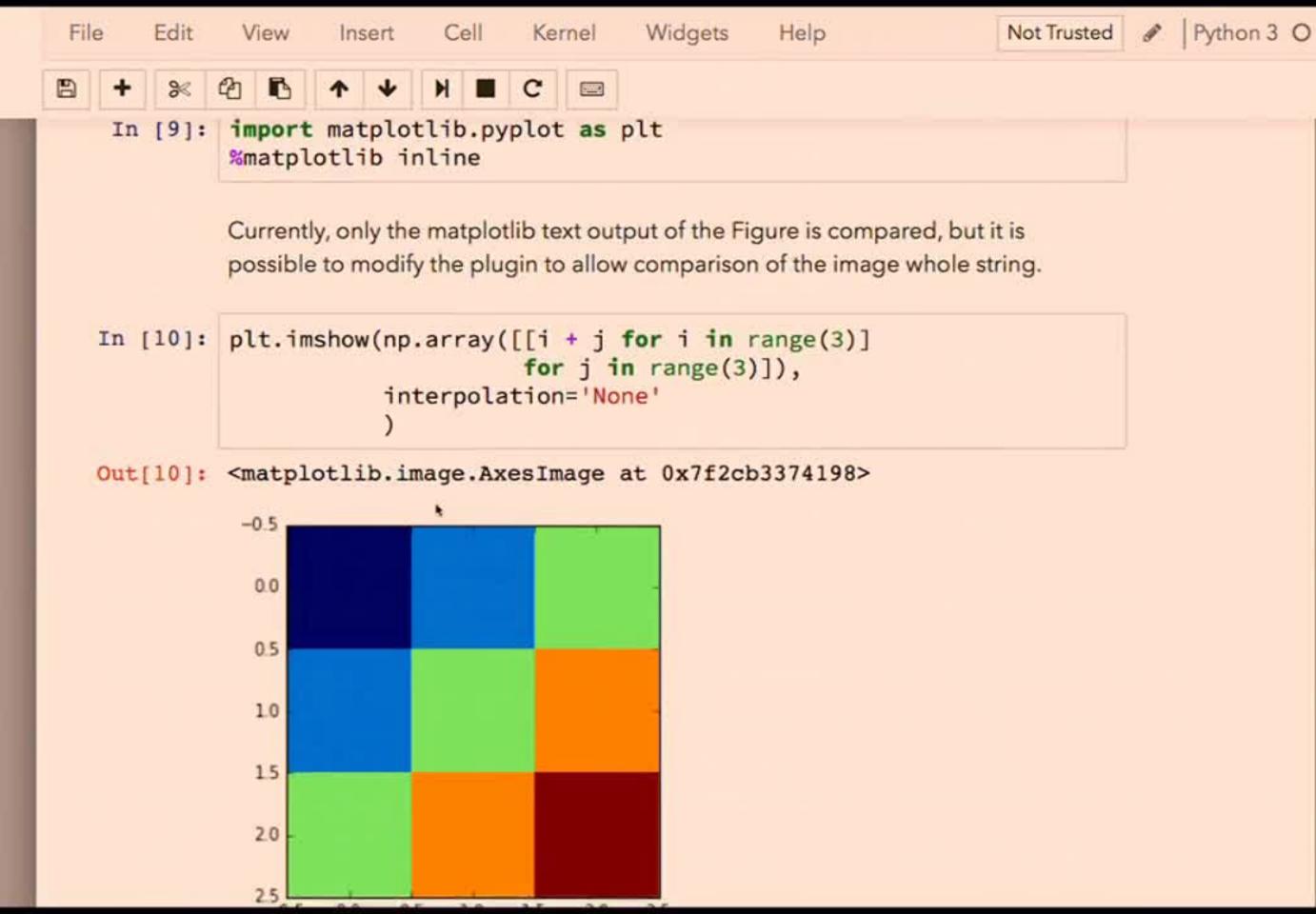


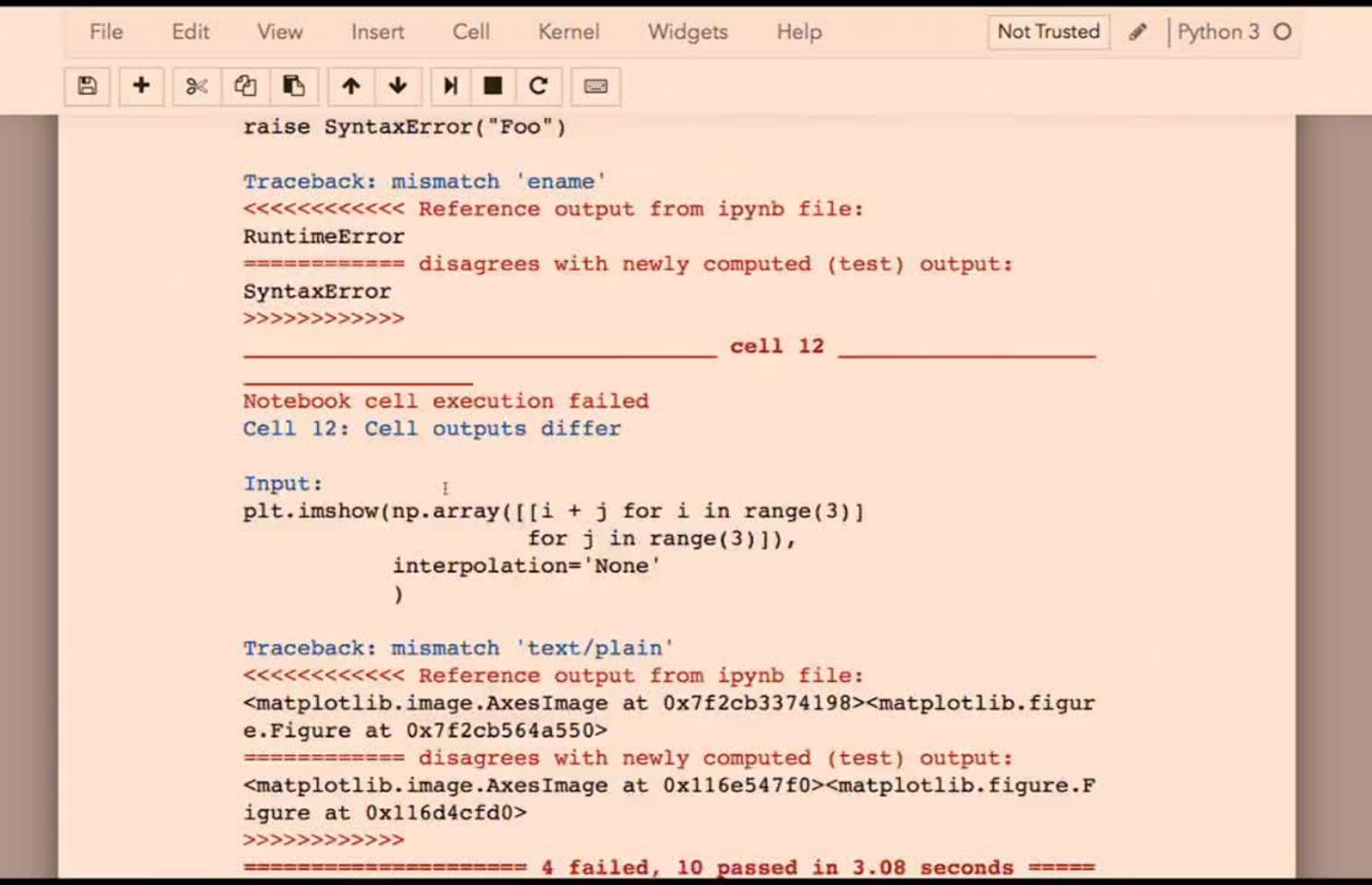
```
while True:
```

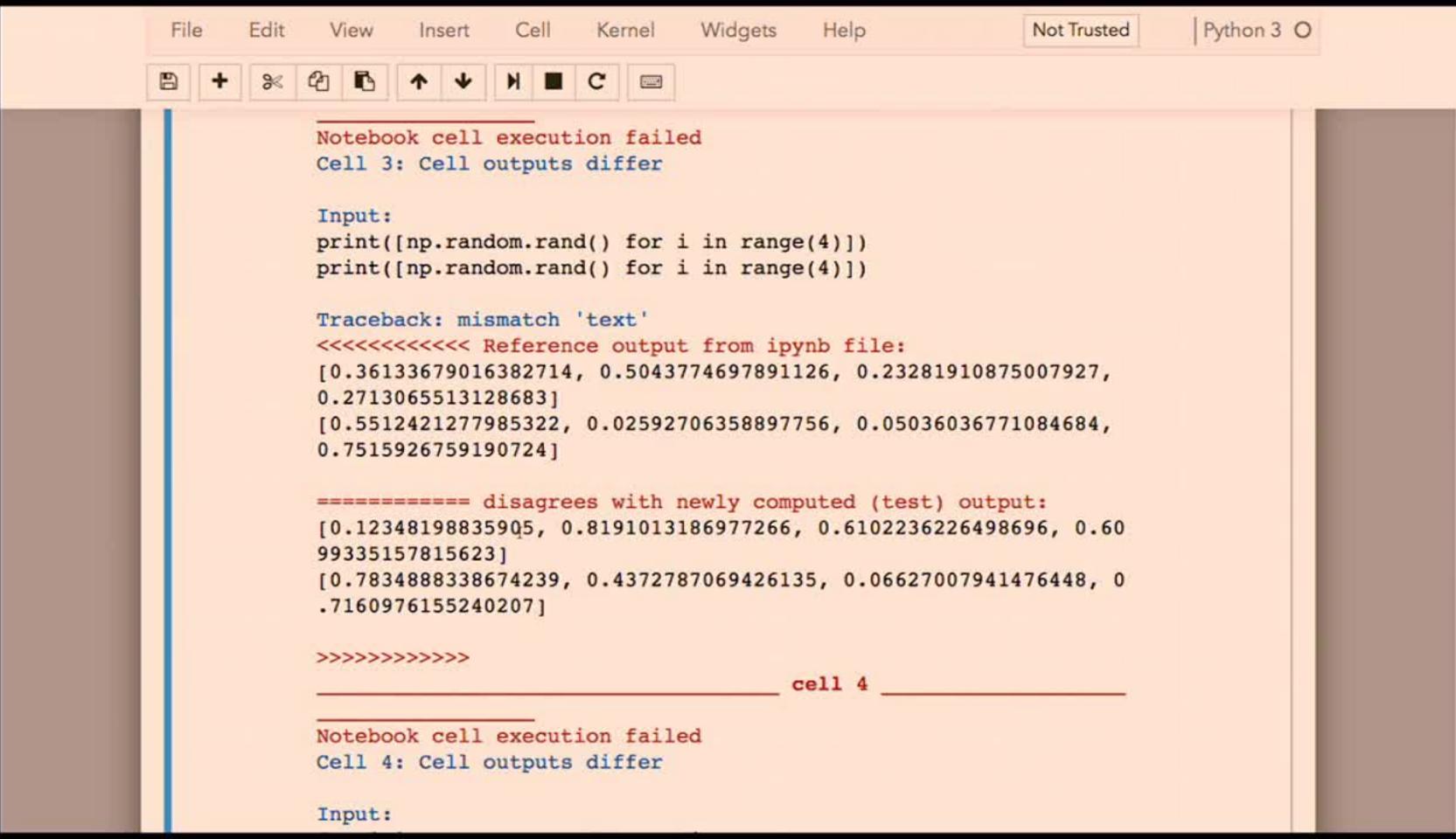
# **Checking exceptions**

Sometimes, we might want to allow a notebook cell to raise an exception, and check that the traceback is as we expect. By annotating the cell with the comment # NBVAL\_RAISES\_EXCEPTION you can indicate that the cell is expected to raise an exception. The full traceback is not compared, but rather just that the raised exception is the same as the stored exception.









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## nbdime - diffing and merging of Jupyter Notebooks

Version: 0.3.0.dev

nbdime provides tools for diffing and merging Jupyter notebooks.

#### Loading Matplotlib demos with %load Cell added I Trython's "tload" magic can be used to load any Matplotlib demo by its UNL: In [411 In [4]: 1000 (mark) 33 iy = func(ix) iy = func(ix) 14 verts = {(a, 0)} + list(zip(ix, iy)) + {(b, 0) 34 verts = [(a, 0)] + list(sip(ix, iy)) + [(b, 0) 35 poly \* Polygon(verts, facecolor\* 0.8 , edgecol 35 poly = Polygon(verts, facecolor='0.6', edgecol 1( ax.add\_patch(poly) 10 ax.add patch(poly) front. Outputs changed Friche

Figure: nbdime example

### Why is nbdime needed?

Jupyter notebooks are useful, rich media documents stored in a plain text JSON format. This format is relatively easy to parse. However, primitive line-based diff and merge tools do not handle well the logical structure of notebook documents. These tools yield diffs like this:

```
$ diff a.ipynb b.ipynb
76,77d75
< "plt.rc('axes', grid=False)\n",
< "plt.rc('axes', facecolor='white')\n",</pre>
```

v: fatest ▼

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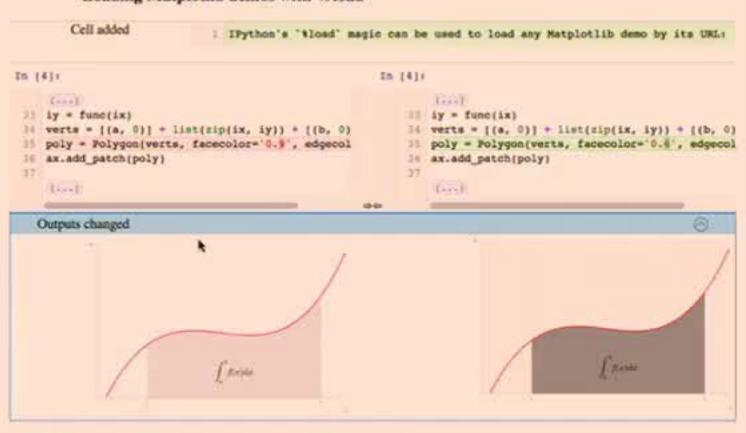
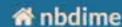


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```
Cell added
                             1 IPython's '%load' magic can be used to load any Matplotlib demo by its URL:
                                                       In [4]:
In [4]:
     1---1
                                                               (---)
 33 iy = func(ix)
                                                            33 iy = func(ix)
                                                           34 verts = [(a, 0)] + list(zip(ix, iy)) + [(b, 0)
 34 verts = [(a, 0)] + list(zip(ix, iy)) + [(b, 0)
 35 poly = Polygon(verts, facecolor='0.9', edgecol
                                                            35 poly = Polygon(verts, facecolor='0.6', edgecol
 36 ax.add patch(poly)
                                                            36 ax.add patch(poly)
     10001
                                                               (---)
   Outputs changed
```



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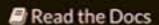
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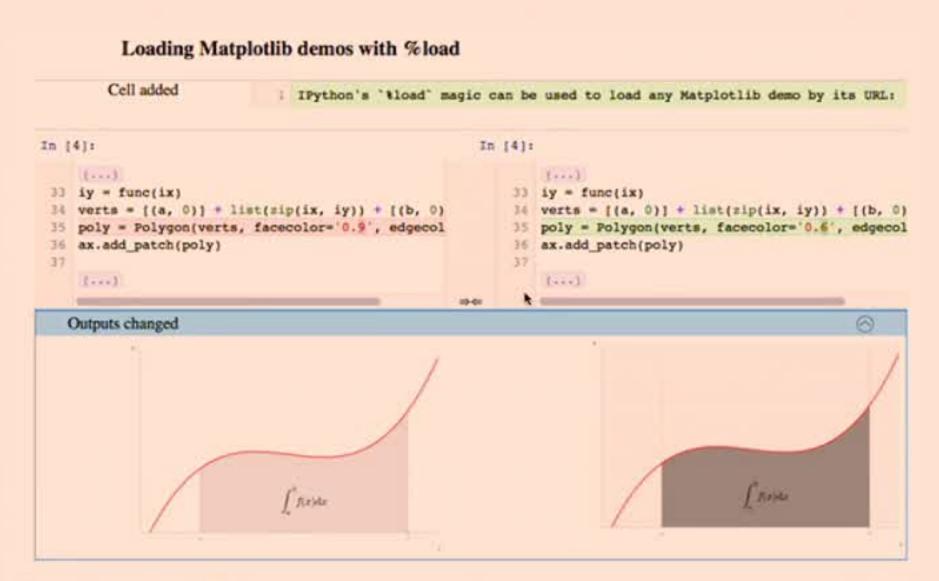
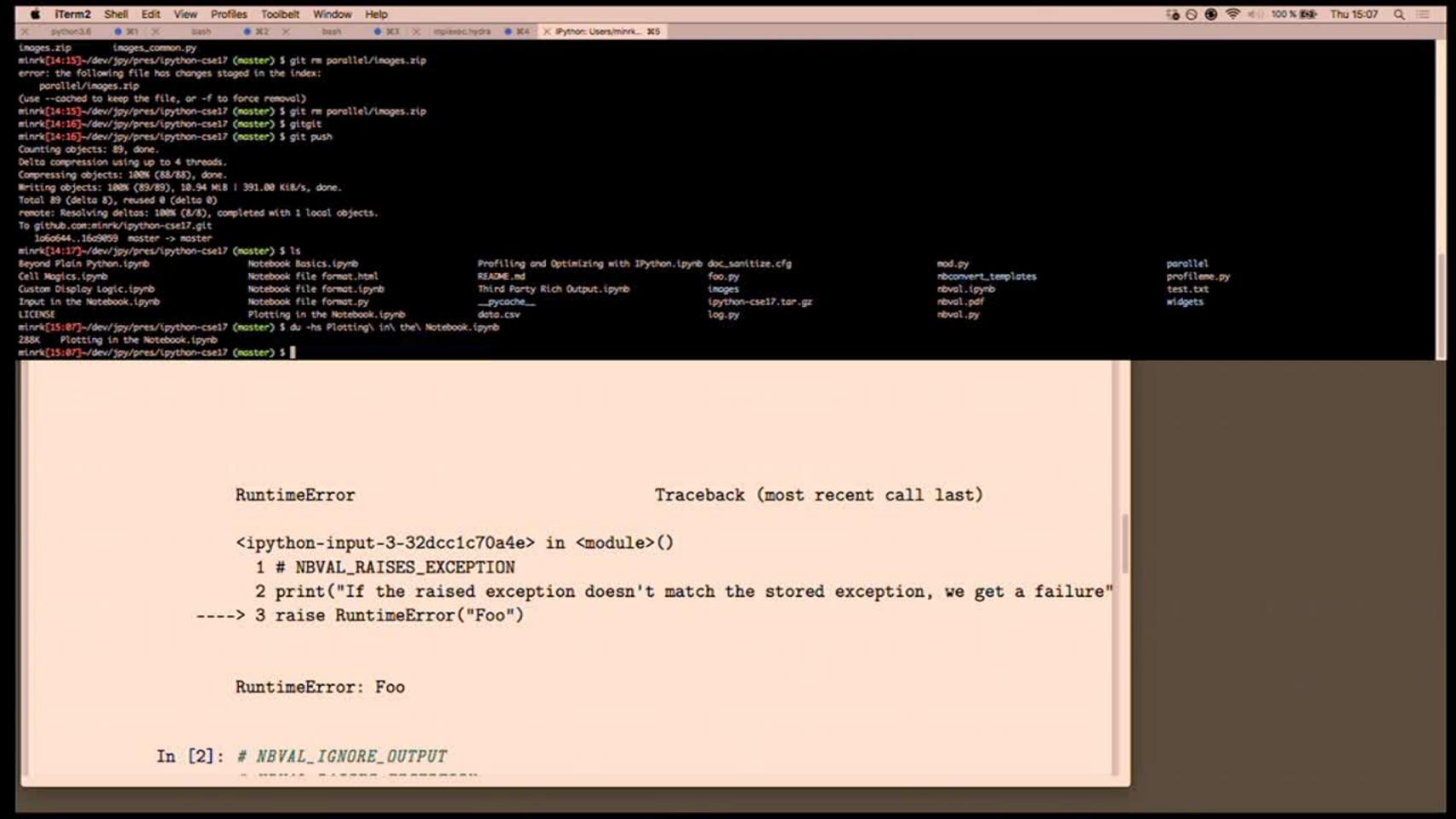


Figure: nbdime example

## Why is nbdime needed?



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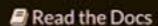
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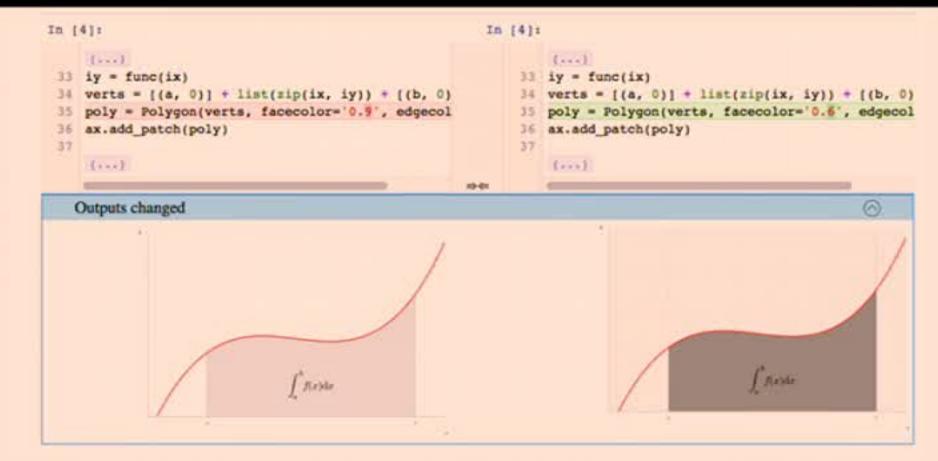


Figure: nbdime's content-aware diff

## Quickstart

To get started with nbdime, install with pip:

```
pip install nbdime
```

And you can be off to the races by diffing notebooks in your terminal with nbdiff:

```
nbdiff notebook_1.ipynb notebook_2.ipynb
```

or viewing a rich web-based rendering of the diff with nbdiff-web:

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# Console commands

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nbdime provides the following CLI commands:

```
nbshow
nbdiff
nbdiff-web
nbmerge
nbmerge-web
mergetool
config-git
```

Pass --help to each command to see help text for the command's usage.

Additional commands are available for Git integration.

### nbshow

nbshow gives you a nice, terminal-optimized summary view of a notebook. You can use it to quickly peek at notebooks without launching the full notebook web application.

```
$ nbshow -s -o c.ipynb
markdown cell 0:
    source:
      # Plotting with Matplotlib

IPython works with the [Matplotlib](http://matplotlib.org/) plotting library,
```

# THO FALLALION AND USAGE Installation □ Console commands nbshow □ Diffing ■ Merging Version control integration Glossary Changes in nbdime Testing diff format Merge details REST API Use cases MAY 8-11, 2017 • AUSTIN, TX Love open source? Early bird pricing on OSCON lasts until March 16. Learn More. Read the Docs v: latest -

nbmerge merges two notebooks with a common parent. If there are conflicts, they are stored in metadata of the destination file. nbmerge will exit with nonzero status if there are any unresolved conflicts.

nbmerge writes the output to stdout by default, so you can use pipes to send the result to a file, or the -o, --output argument to specify a file in which to save the merged notebook.

Because there are several categories of data in a notebook (such as input, output, and metadata), nbmerge has several ways to deal with conflicts, and can take different actions based on the type of data with the conflict.

#### Important

Conflict-resolution in nbmerge is under active development and is subject to change.

Ð

The -m, --merge-strategy option lets you select a global strategy to use. The following options are currently implemented:

#### inline

This is the default. Conflicts in input and output are recorded with conflict markers, while conflicts on metadata are stored in the appropriate metadata (actual values are kept as their base values).

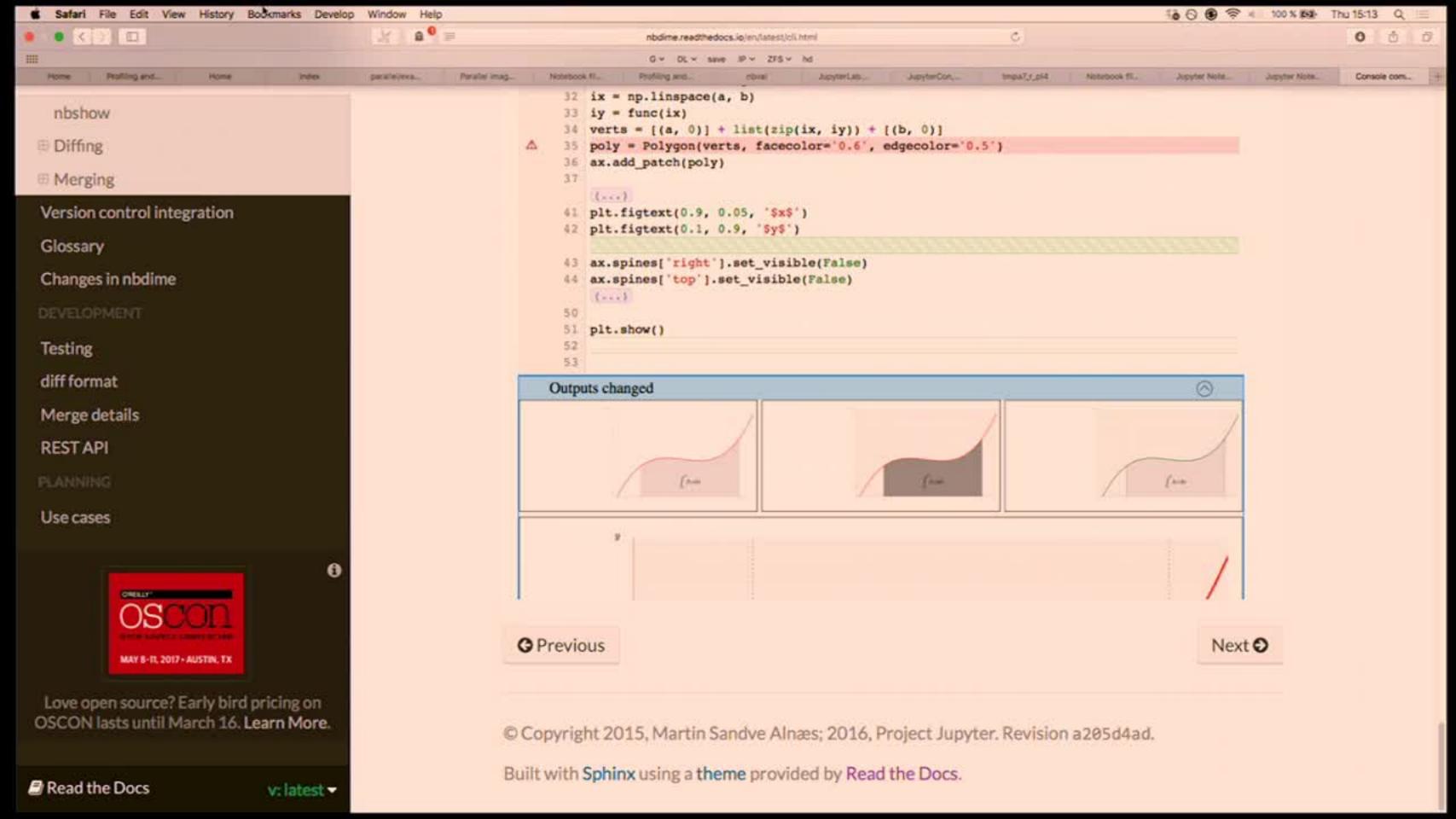
This gives you a valid notebook that you can open in your usual notebook editor and resolve conflicts by hand, just like you might for a regular source file in your text editor.

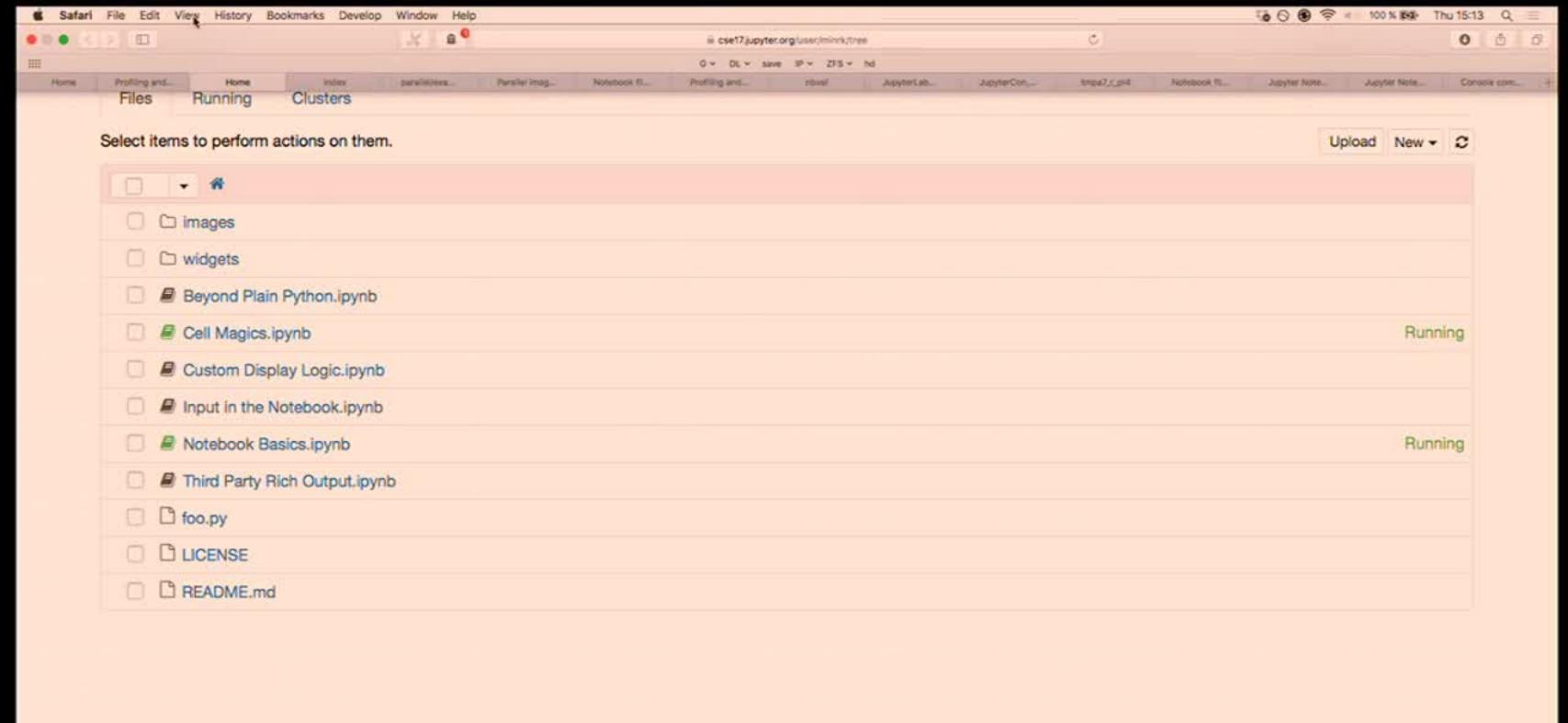
#### use-base

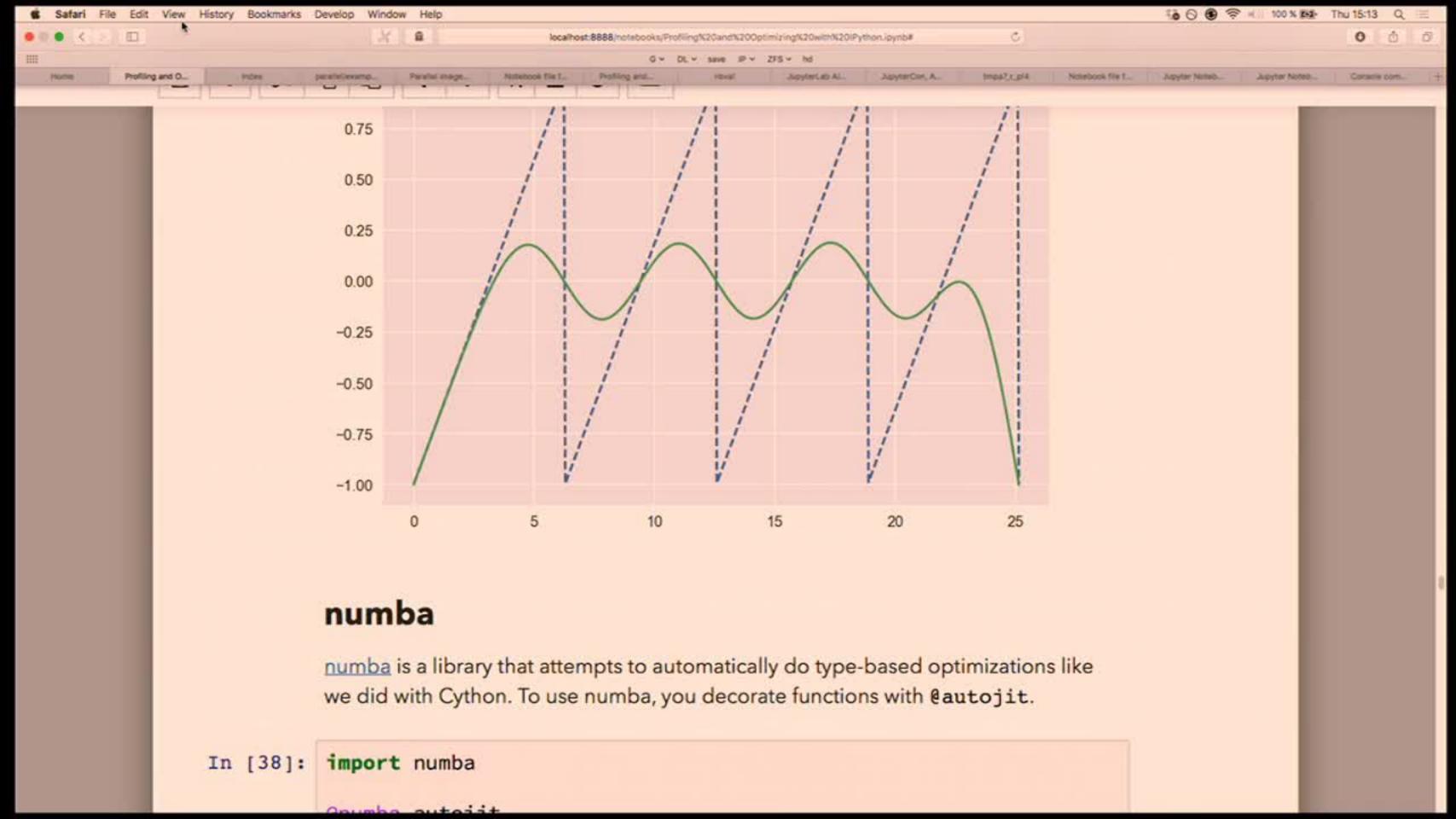
When a conflict is encountered, use the value from the base notebook.

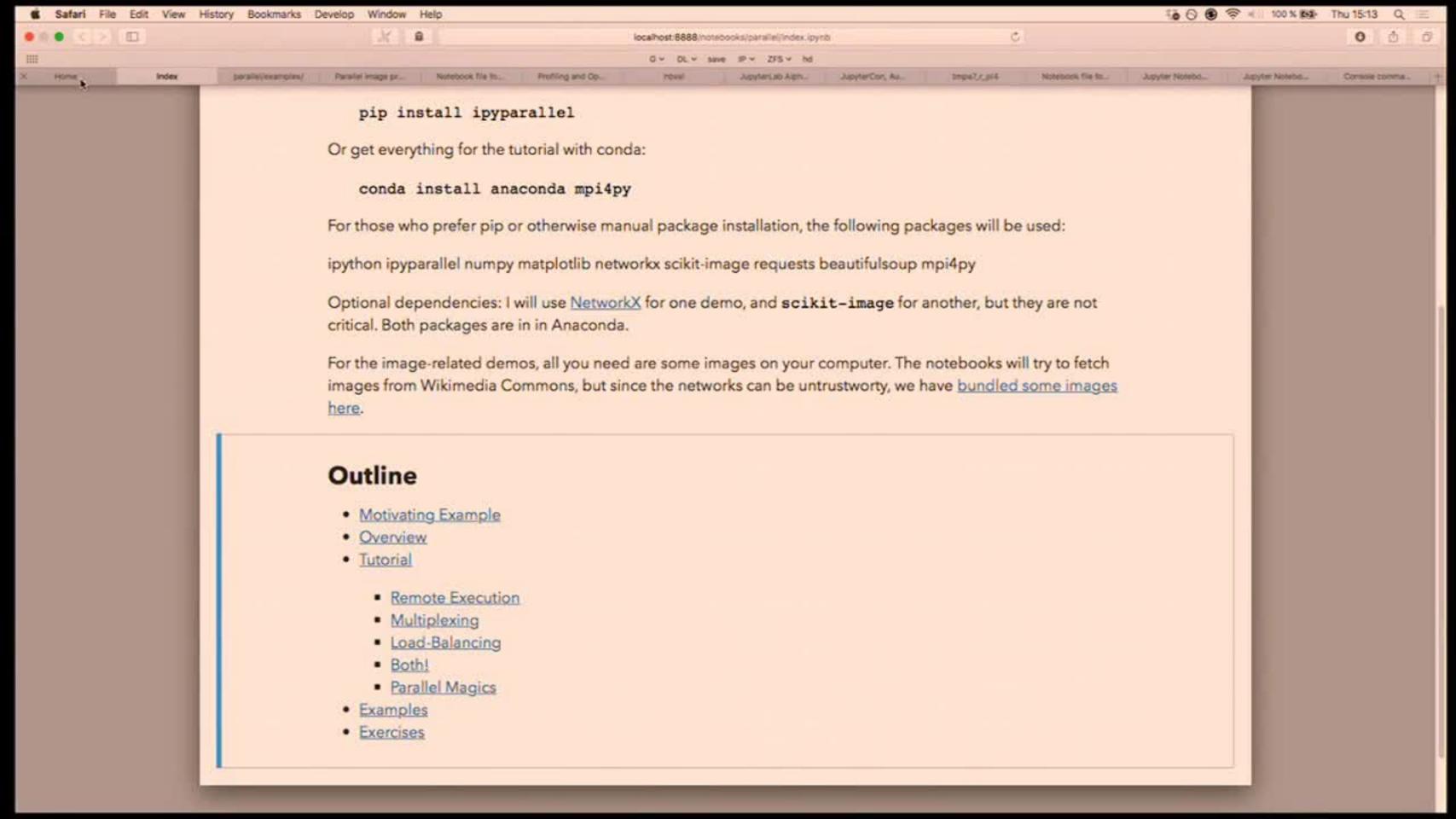
#### use-local

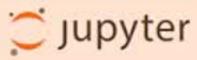
When a conflict is encountered, use the value from the local notebook.











Files Running **IPython Clusters** Select items to perform actions on them. Upload New ▼ 2 / parallel Last Modified ↑ Name 1 D .. seconds ago an hour ago n examples exercises an hour ago ☐ ☐ figs an hour ago □ soln an hour ago an hour ago tutorial download-images.ipynb an hour ago Index.ieynb Running an hour ago Overview.ipynb an hour ago Performance.ipynb an hour ago Summary.ipynb an hour ago 5000-8.txt an hour ago



#### Interactive (parallel) Python

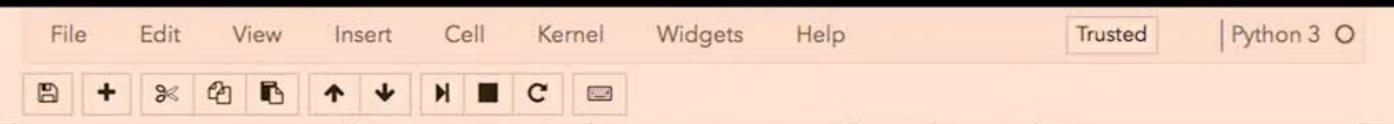
#### Installation and dependencies

You will need ipyparallel >= 5.x, and pyzmq  $\ge 13$ . To use the demo notebooks, you will also need tornado  $\ge 4$ . I will also make use of numpy and matplotlib. If you have Canopy or Anaconda, you already have all of these.

Quick one-line install for IPython and its dependencies:

pip install ipyparallel

Or get everything for the tutorial with conda:



notebooks will try to fetch images from Wikimedia Commons, but since the networks can be untrustworty, we have <u>bundled some images here</u>.

#### **Outline**

- Motivating Example
- Overview
- Tutorial
  - Remote Execution
  - Multiplexing
  - Load-Balancing
  - Both!
  - Parallel Magics
- Examples
- Exercises



To get a sense of what IPython.parallel might be used for, we start with an example of some batch processing of image files with <u>scikit-image</u>. We will revisit pieces of this example as we learn about the different components of IPython.

```
In []:
    import sys
    import requests
    from zipfile import ZipFile, BadZipFile
    from ipywidgets import IntProgress
    from IPython.display import display
```



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In []: import sys
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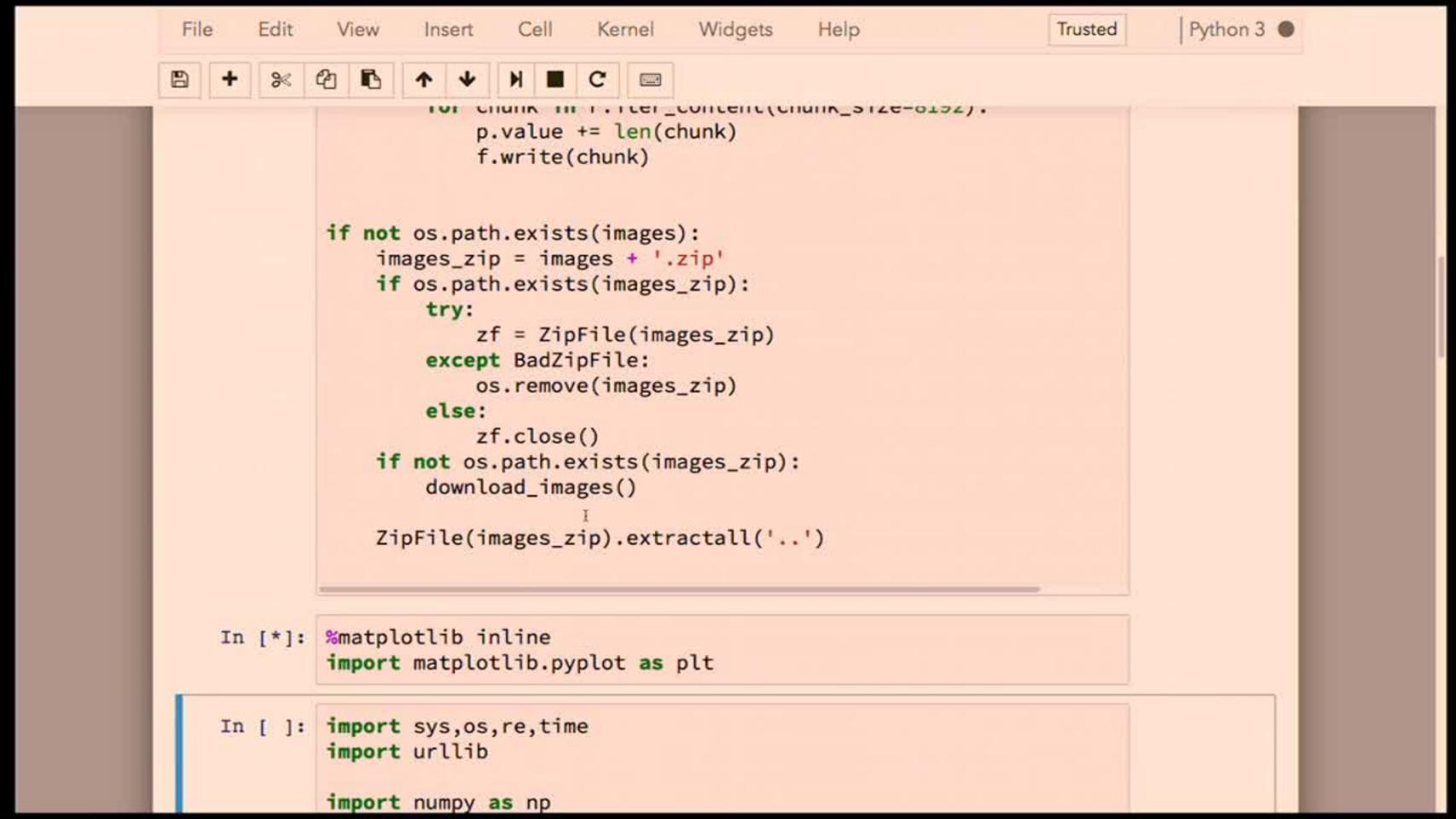
images = os.path.join('...', 'images')
    images_url = "https://s3.amazonaws.com/ipython-parallel-data/ima"
```

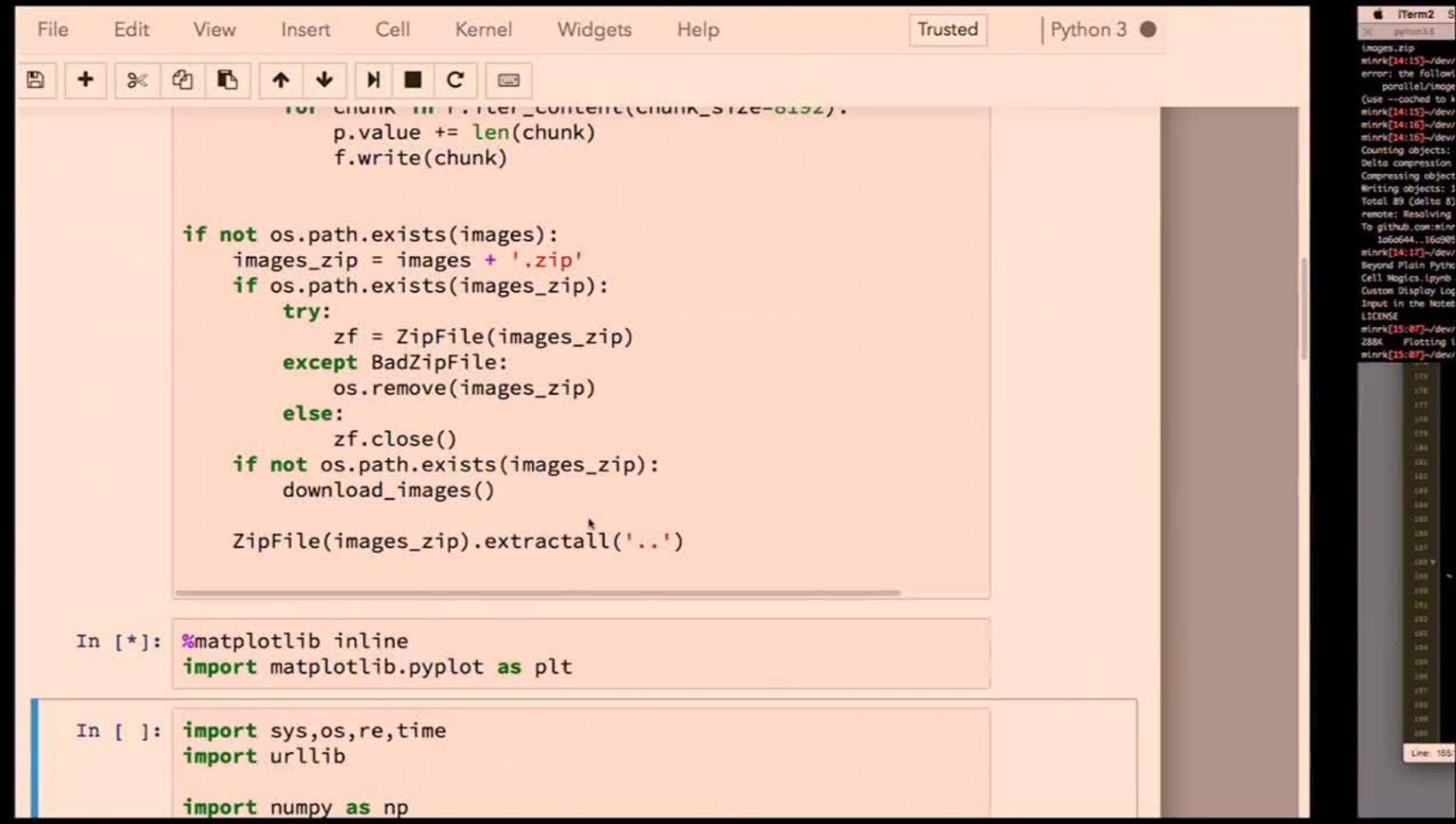
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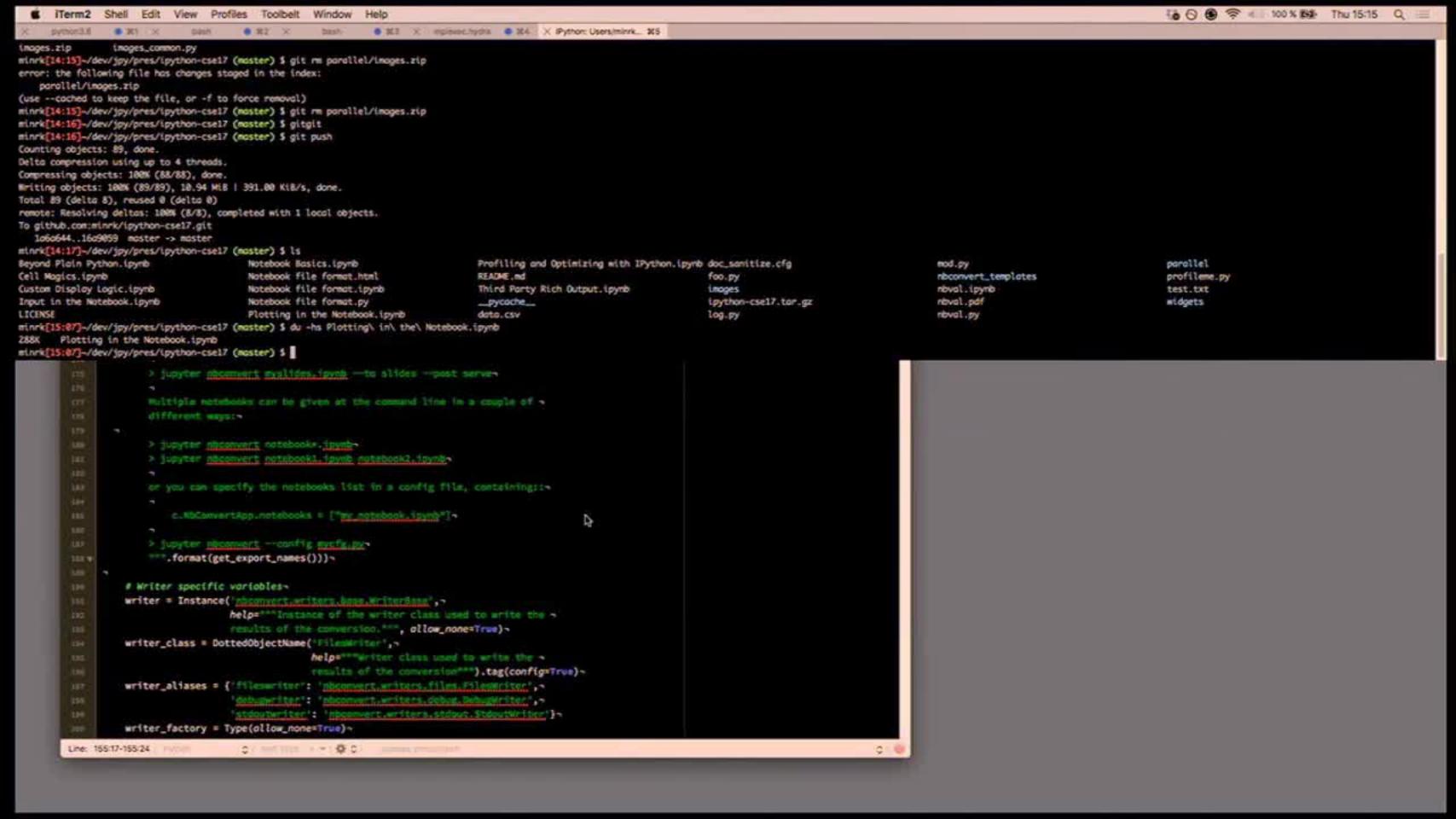
```
In []: import sys
    import requests|
    from zipfile import ZipFile, BadZipFile
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images = os.path.join('...', 'images')
    images_url = "https://s3.amazonaws.com/ipython-parallel-data/ima

def download images():
```







To get a sense of what IPython.parallel might be used for, we start with an example of some batch processing of image files with <u>scikit-image</u>. We will revisit pieces of this example as we learn about the different components of IPython.

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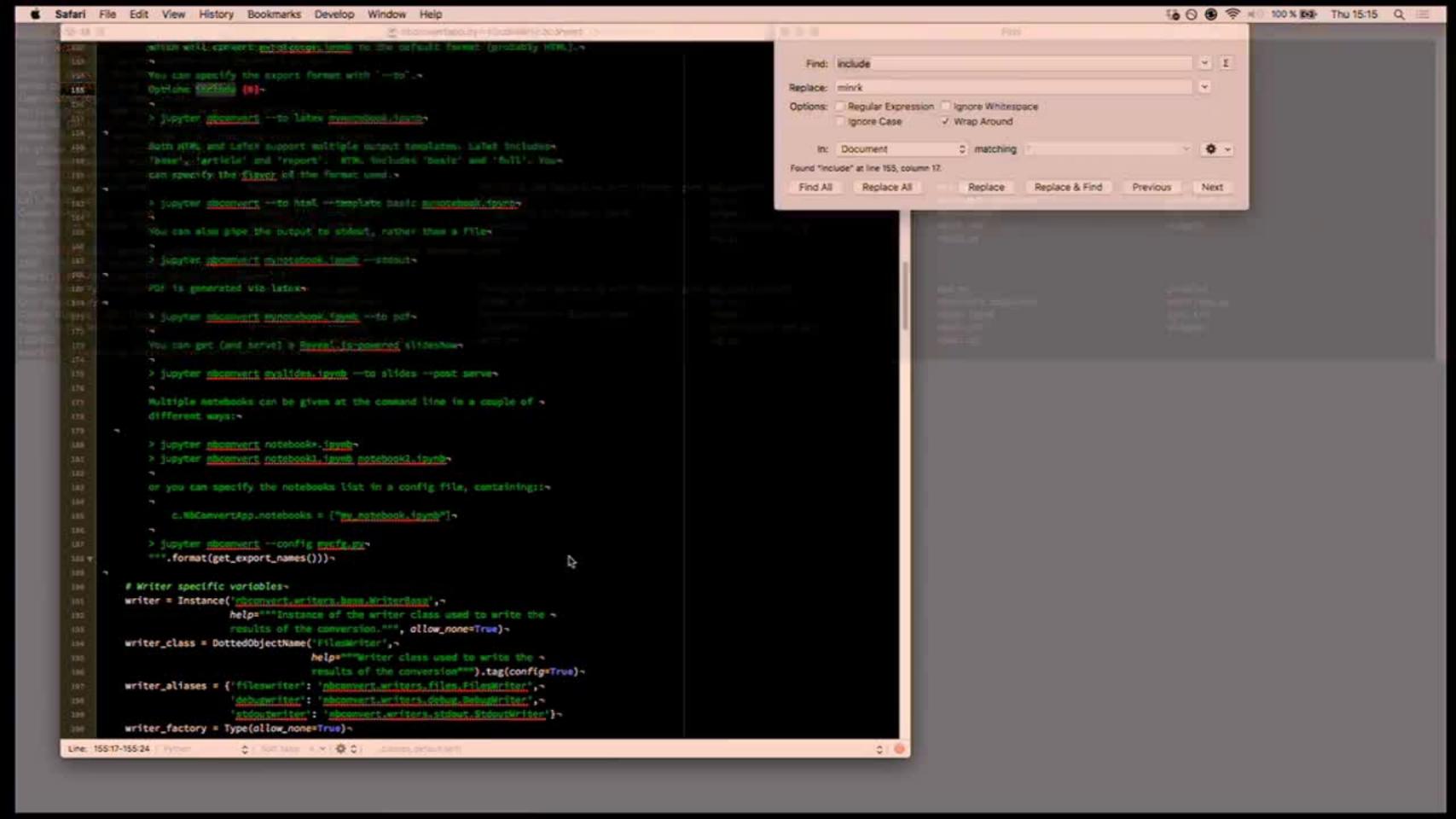
images = os.path.join('..', 'images')
images_url = "https://s3.amazonaws.com/ipython-parallel-data/images_url = "https://s3.amazonaws.com/ipython-parallel-data/images_url = requests.get(images_url, stream=True)
content_length = r.headers.get('content-length')
print("Downloading images")
sys.stdout.flush()
```

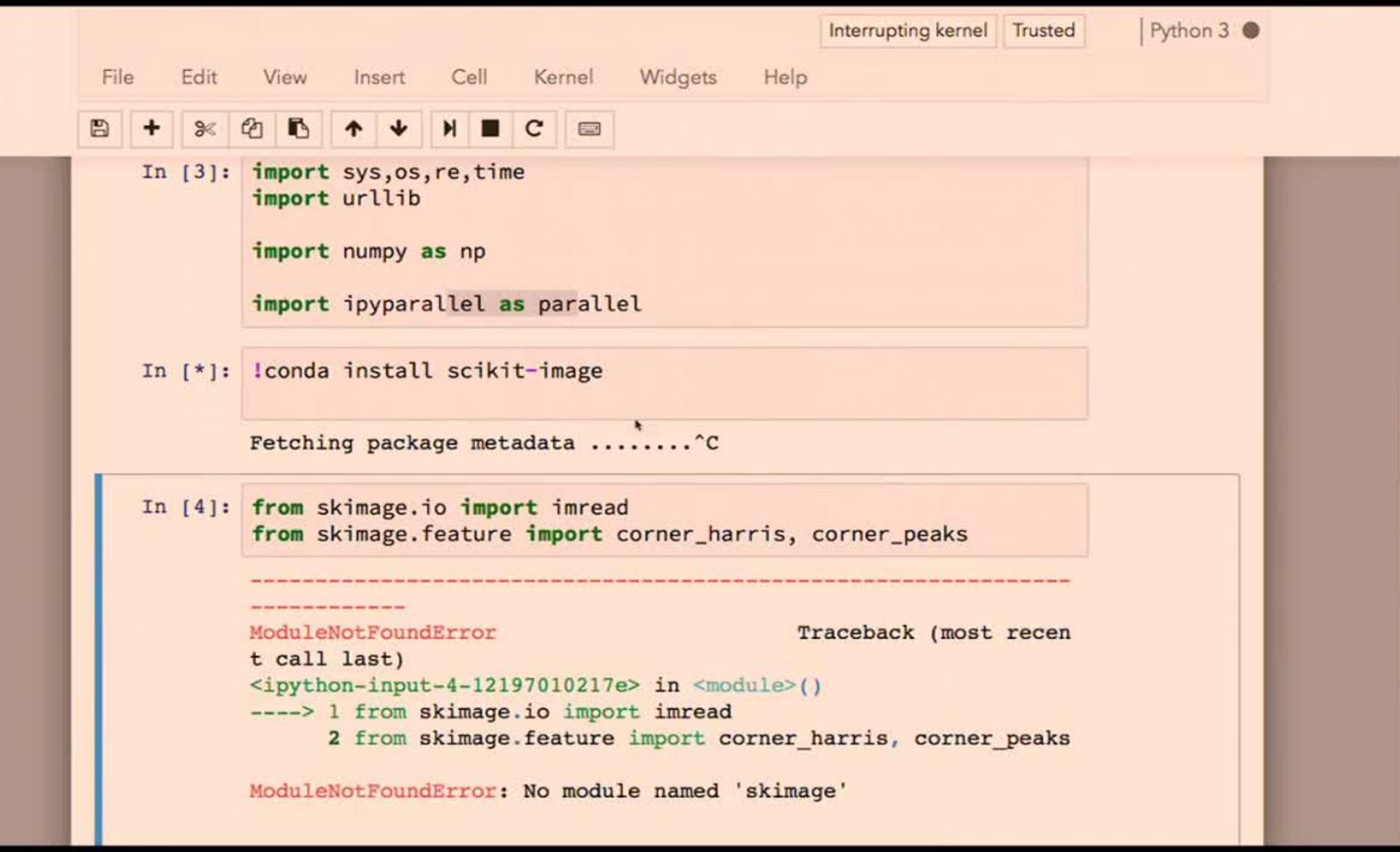
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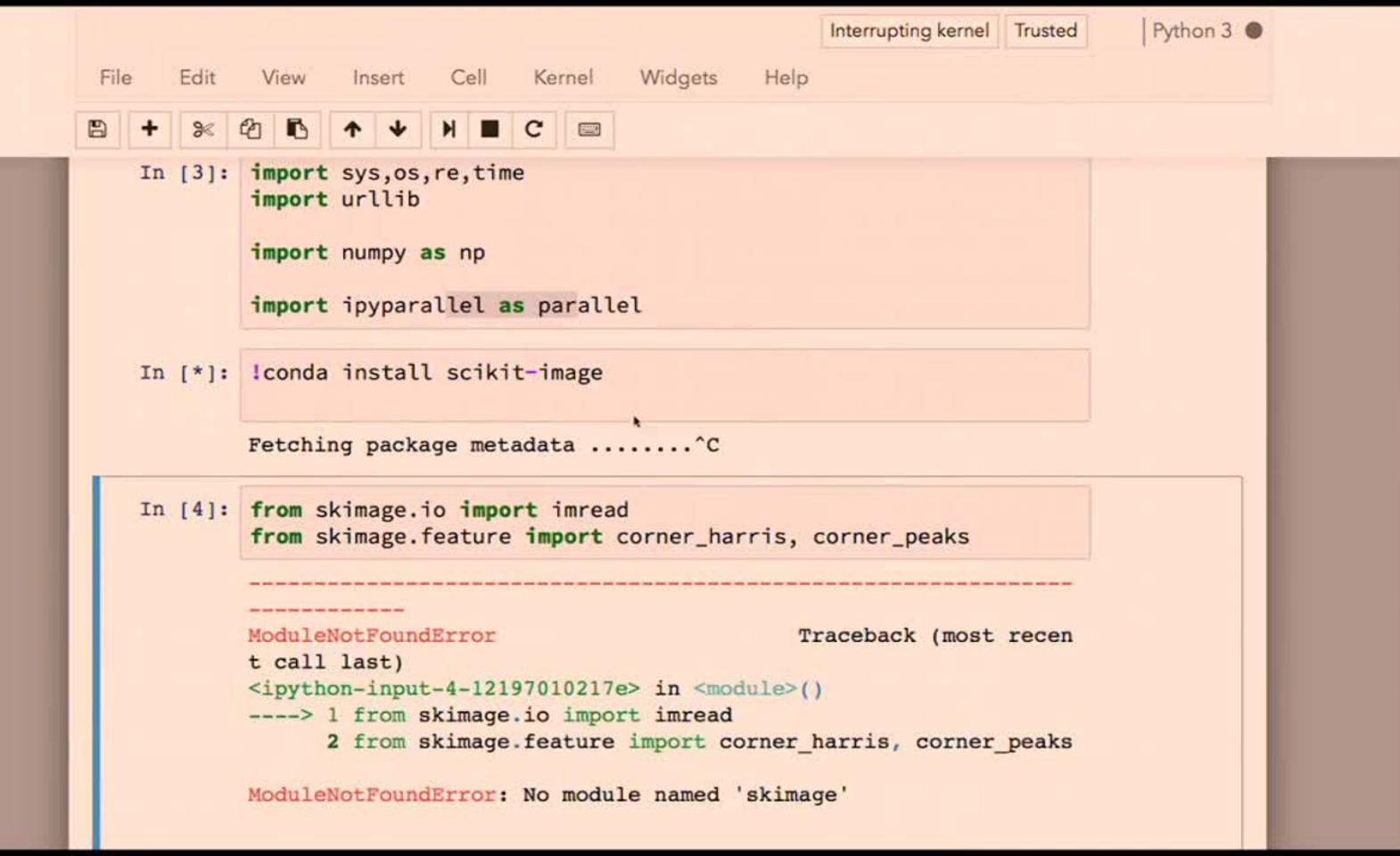
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        import sys
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        images = os.path.join('...', 'images')
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        def download_images():
            r = requests.get(images_url, stream=True)
            content_length = r.headers.get('content-length')
            print("Downloading images")
            sys.stdout.flush()
            p = IntProgress(max=content_length)
            display(p)
            with open(images_zip, 'wb') as f:
```

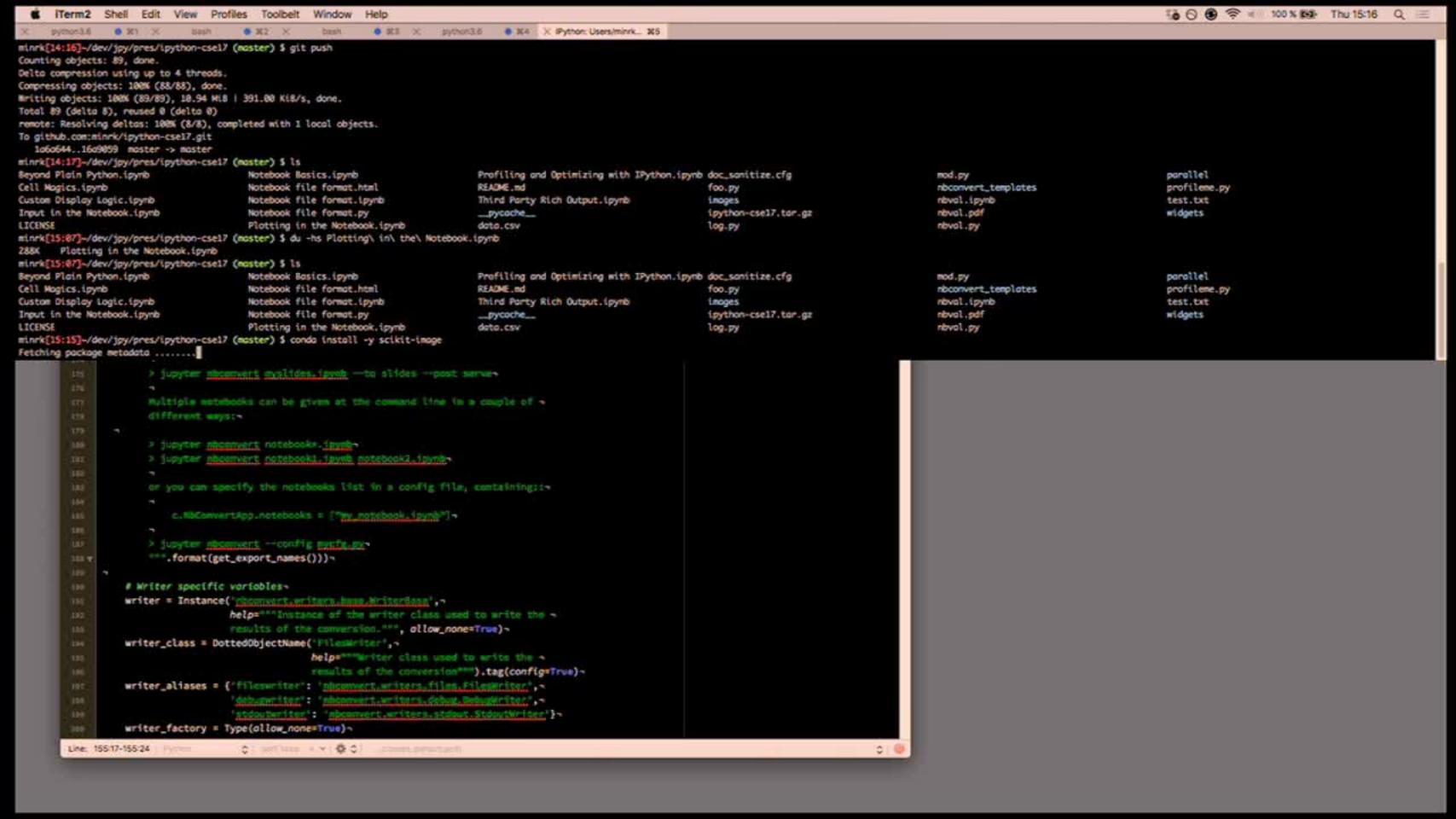
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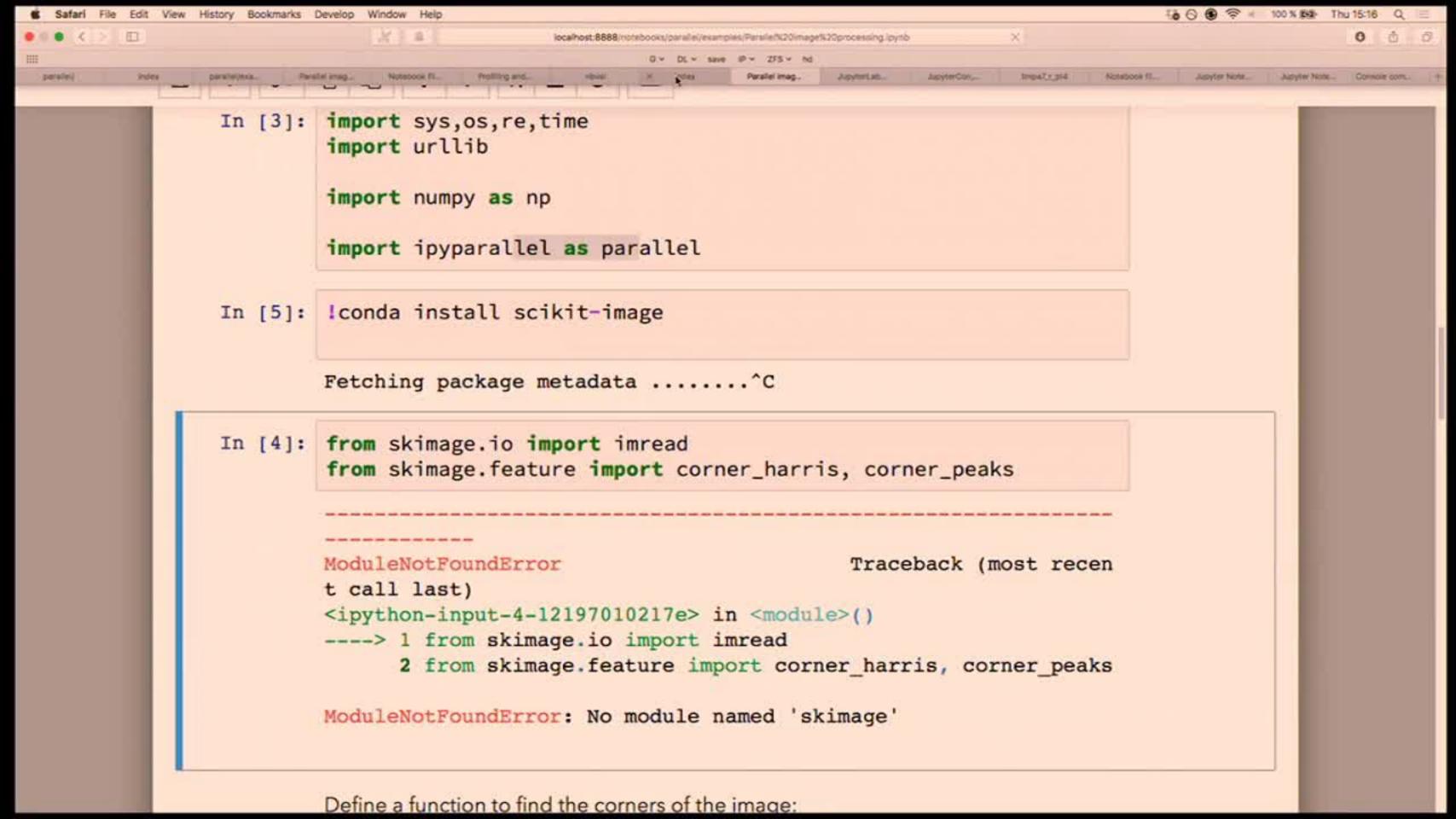
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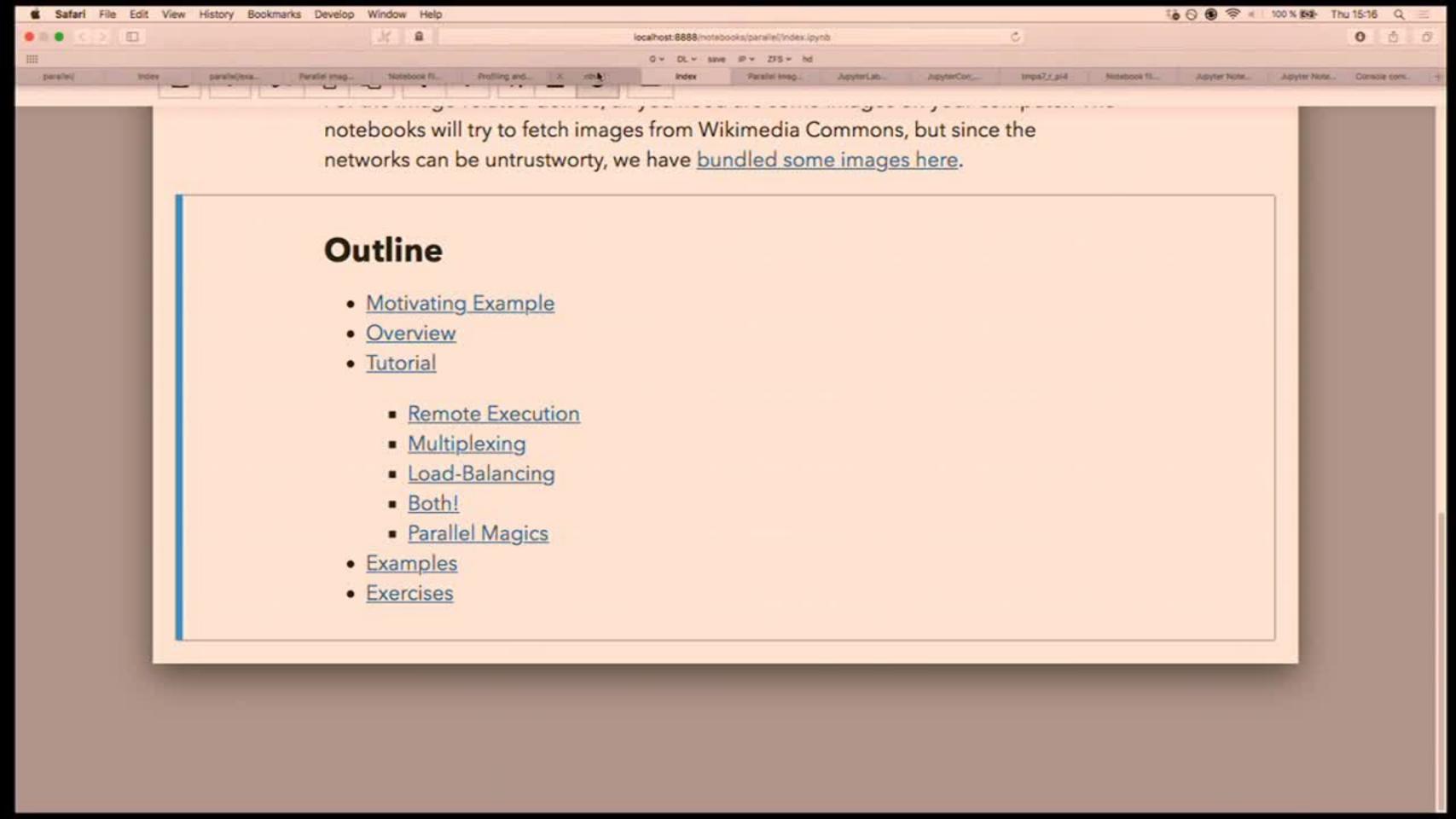


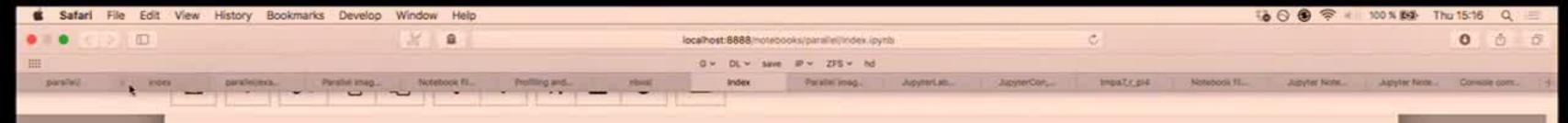












#### Interactive (parallel) Python

#### Installation and dependencies

You will need ipyparallel >= 5.x, and pyzmq  $\ge 13$ . To use the demo notebooks, you will also need tornado  $\ge 4$ . I will also make use of numpy and matplotlib. If you have Canopy or Anaconda, you already have all of these.

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Or get everything for the tutorial with conda:

conda install anaconda mpi4py

For those who prefer pip or otherwise manual package installation, the following packages will be used:

ipython ipyparallel numpy matplotlib networkx scikit-image requests beautifulsoup mpi4py

## Interactive monitoring of a parallel MPI simulation with the IPython Notebook

```
In [3]: %matplotlib inline
    import numpy as np
    import matplotlib.pyplot as plt

    from IPython.display import display
    from ipyparallel import Client, error

    cluster = Client(profile="mpi")
    view = cluster[:]
    view.block = True
    e0 = cluster[0]
    e0.activate('0')
In [4]: cluster.ids
```



## Interactive monitoring of a parallel MPI simulation with the IPython Notebook

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from IPython.display import display
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## Interactive monitoring of a parallel MPI simulation with the IPython Notebook

```
In [22]: %matplotlib inline
         import numpy as np
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         from IPython.display import display
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         cluster = Client(profile="mpi")
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         e0 = cluster[0]
         e0.activate('0')
 In [4]: cluster.ids
 Out[4]: [0, 1, 2, 3]
```

Now, we load the MPI libraries into the engine namespaces, and do a simple



```
Out[23]: [0, 1, 2, 3]
```

Now, we load the MPI libraries into the engine namespaces, and do a simple printing of their MPI rank information to verify that all nodes are operational and they match our cluster's real capacity.

Here, we are making use of IPython's special **%%px** cell magic, which marks the entire cell for parallel execution. This means that the code below will not run in this notebook's kernel, but instead will be sent to all engines for execution there. In this way, IPython makes it very natural to control your entire cluster from within the notebook environment:

We write a utility that reorders a list according to the mpi ranks of the engines, since all gather operations will return data in engine id order, not in MPI rank order. We'll need this later on when we want to reassemble in IPython data structures coming from all the engines: IPython will collect the data ordered by engine ID, but our code creates data structures based on MPI rank, so we need to map from one indexing scheme to the other. This simple function does the job:

```
In [25]: ranks = view['rank']
    rank_indices = np.argsort(ranks)

def mpi_order(seq):
    """Return elements of a sequence ordered by MPI rank.

The input sequence is assumed to be ordered by engine ID."""
    return [seq[x] for x in rank_indices]
```

#### **MPI simulation example**

[stdout:3] MPI rank: 3/4

This is our 'simulation' a toy example that computes  $\sin(f(x^2 + v^2))$  for a slowly



```
# remotely for interactive introspection
global j, Z, nx, nyt
freqs = np.linspace(0.6, 1, nsteps)
for j in range(nsteps):
    nx, ny = 2+j//4, 2+j//2//mpi.size
    nyt = mpi.size*ny
   XaxI= np.linspace(xmin, xmax, nx)
    Yax = np.linspace(ymin+rank*dy, ymin+(rank+1)*dy, ny, en
    X, Y = np.meshgrid(Xax, Yax)
    f = freqs[j]
    Z = np.cos(f*(X**2 + Y**2))
    # We add a small delay to simulate that a real-world com
    # would take much longer, and we ensure all nodes are sy
    time.sleep(delay)
    # The stop flag can be set remotely via IPython, allowin
    # cleanly stopped from the outside
    if stop:
        break
```

#### IPython tools to interactively monitor and plot the MPI results

We now define a local (to this notebook) plotting function that fetches data from the engines' global namespace. Once it has retrieved the current state of the relevant



### IPython tools to interactively monitor and plot the MPI results

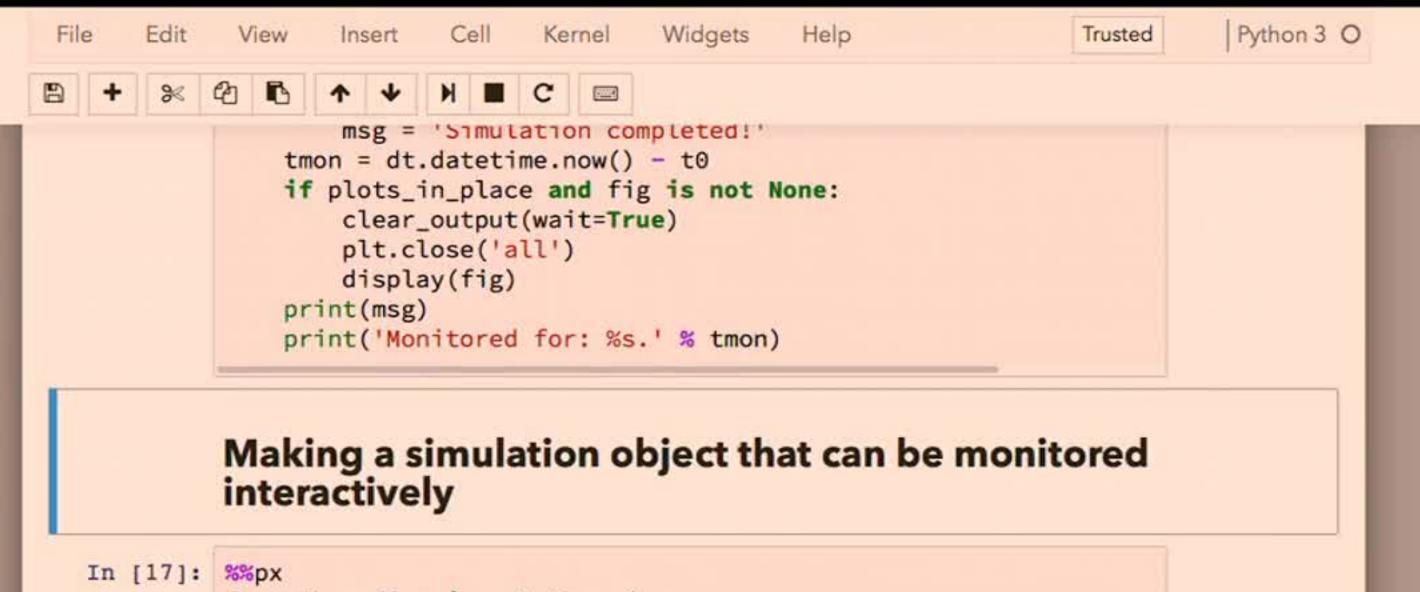
break

We now define a local (to this notebook) plotting function that fetches data from the engines' global namespace. Once it has retrieved the current state of the relevant variables, it produces and returns a figure:

```
In [14]: from IPython.display import clear_output

def plot_current_results(in_place=True):
    """Makes a blocking call to retrieve remote data and display
    as a contour plot.

Parameters
    -----
    in_place : bool
        By default it calls clear_output so that new plots repla
        to False to allow keeping of all previous outputs.
    """
```



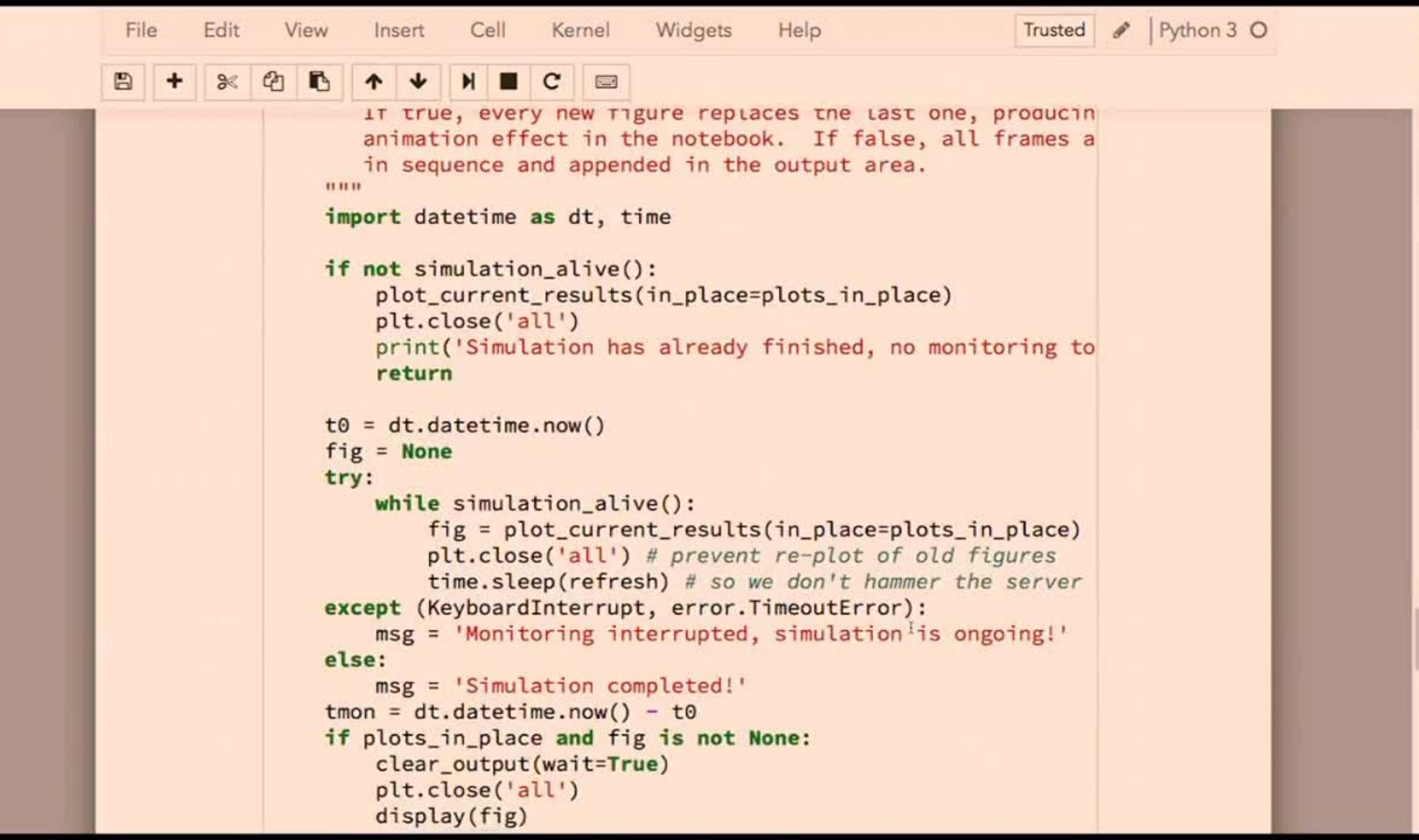
```
In [17]: %%px
    from threading import Thread
    stop = False
    nsteps = 100
    delay=0.5
# Create a thread wrapper for the simulation. The target must be
# function so we wrap the call to 'simulation' in a simple lambd
    simulation_thread = Thread(target = lambda : simulation())
# Now we actually start the simulation
    simulation_thread.start()
```

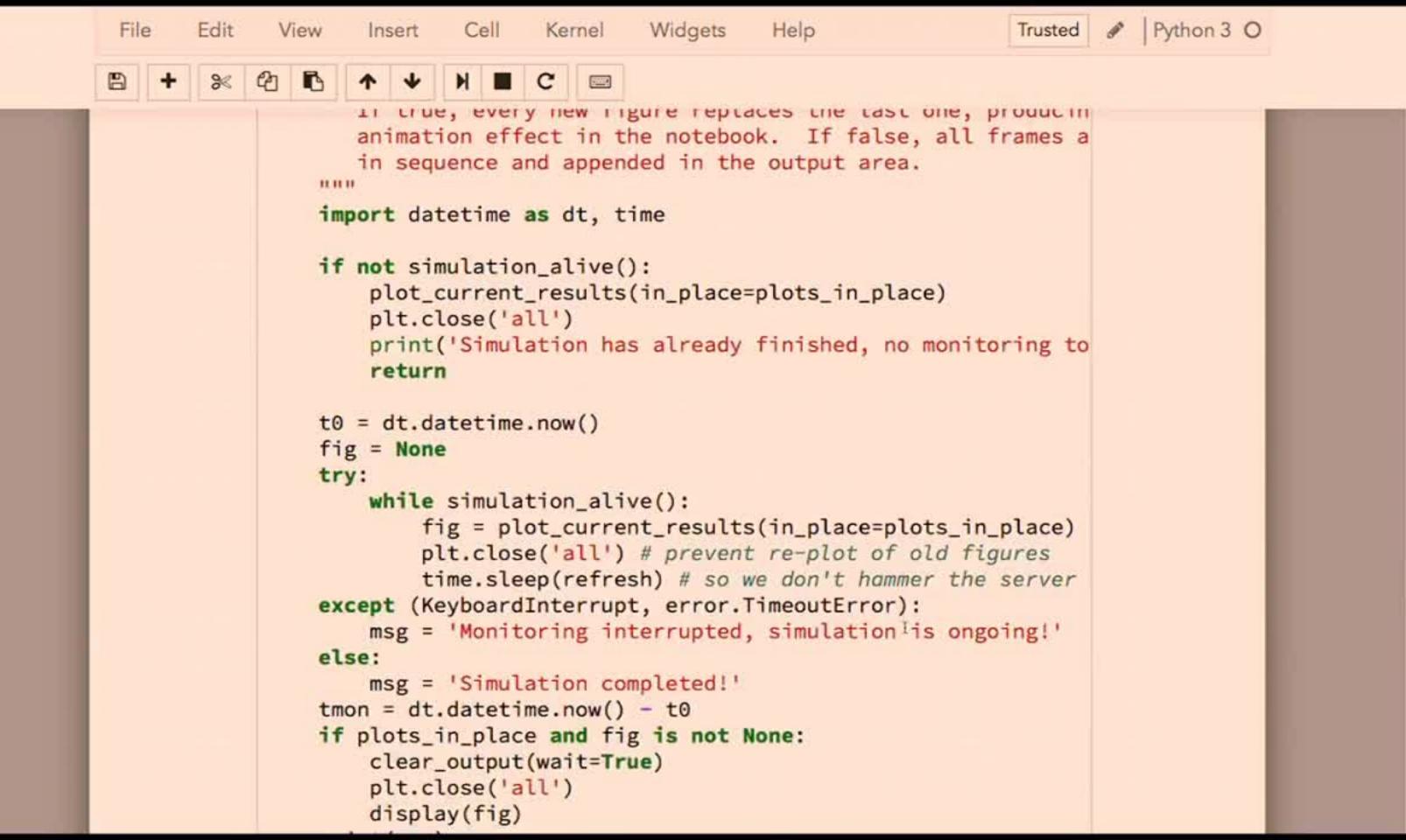
In [18]: monitor\_simulation(refresh=1);

Python 3 O

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```

Mesh: 17 x 36, step 61/100



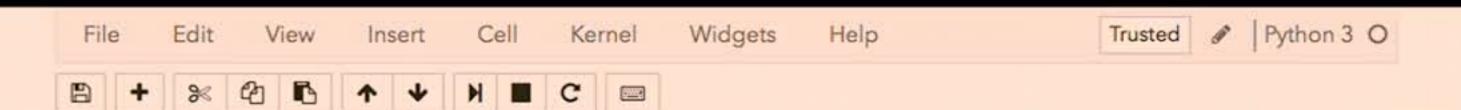


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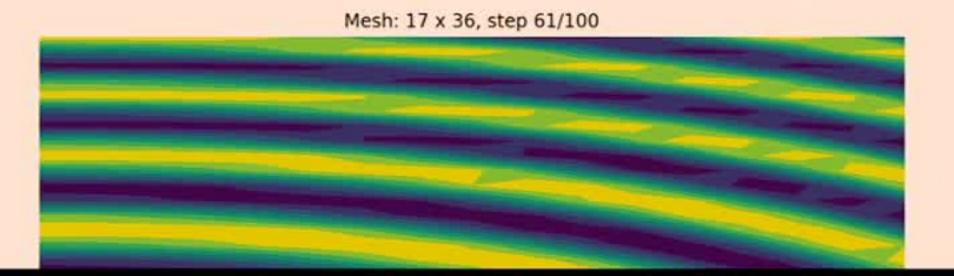
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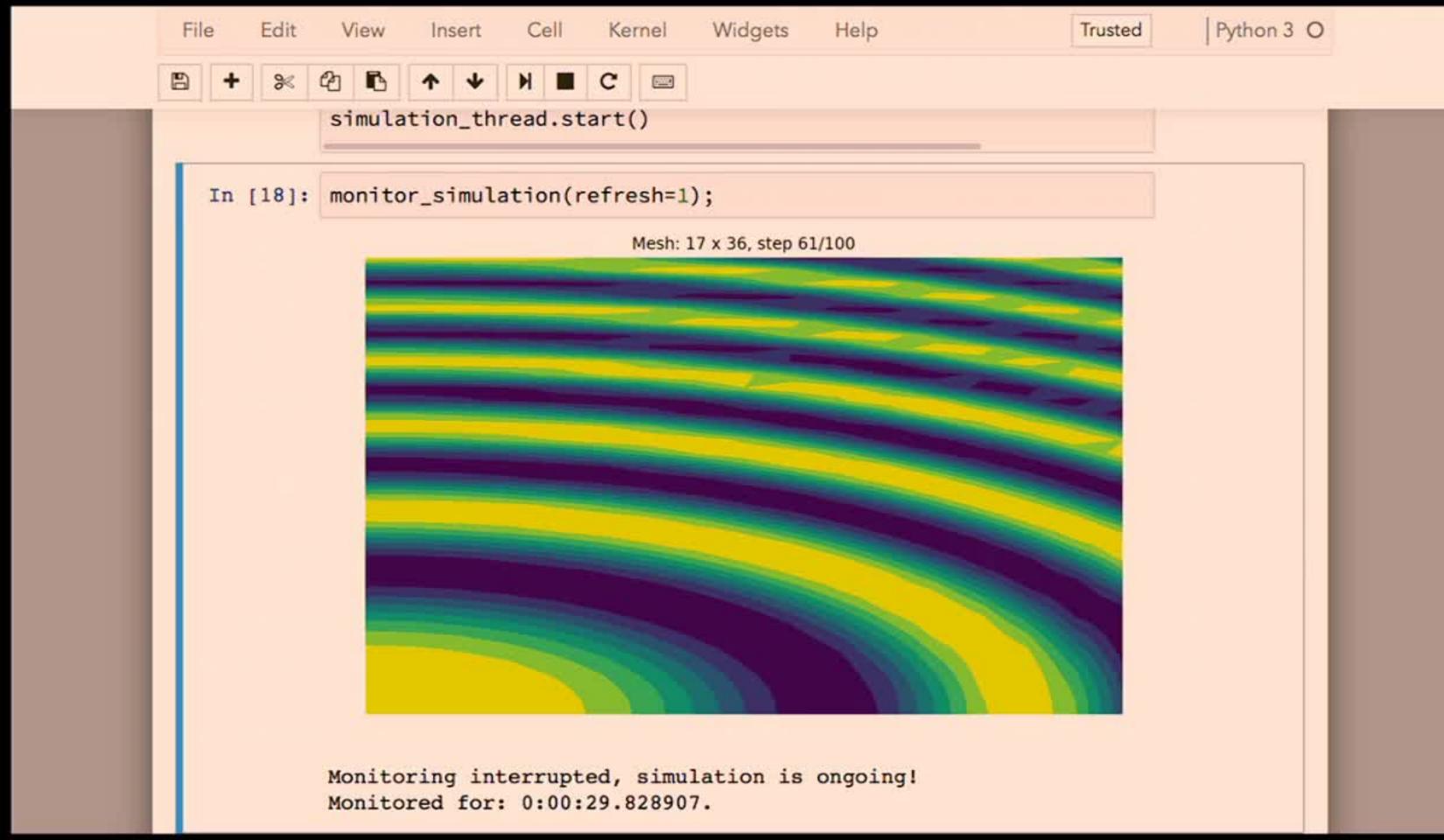
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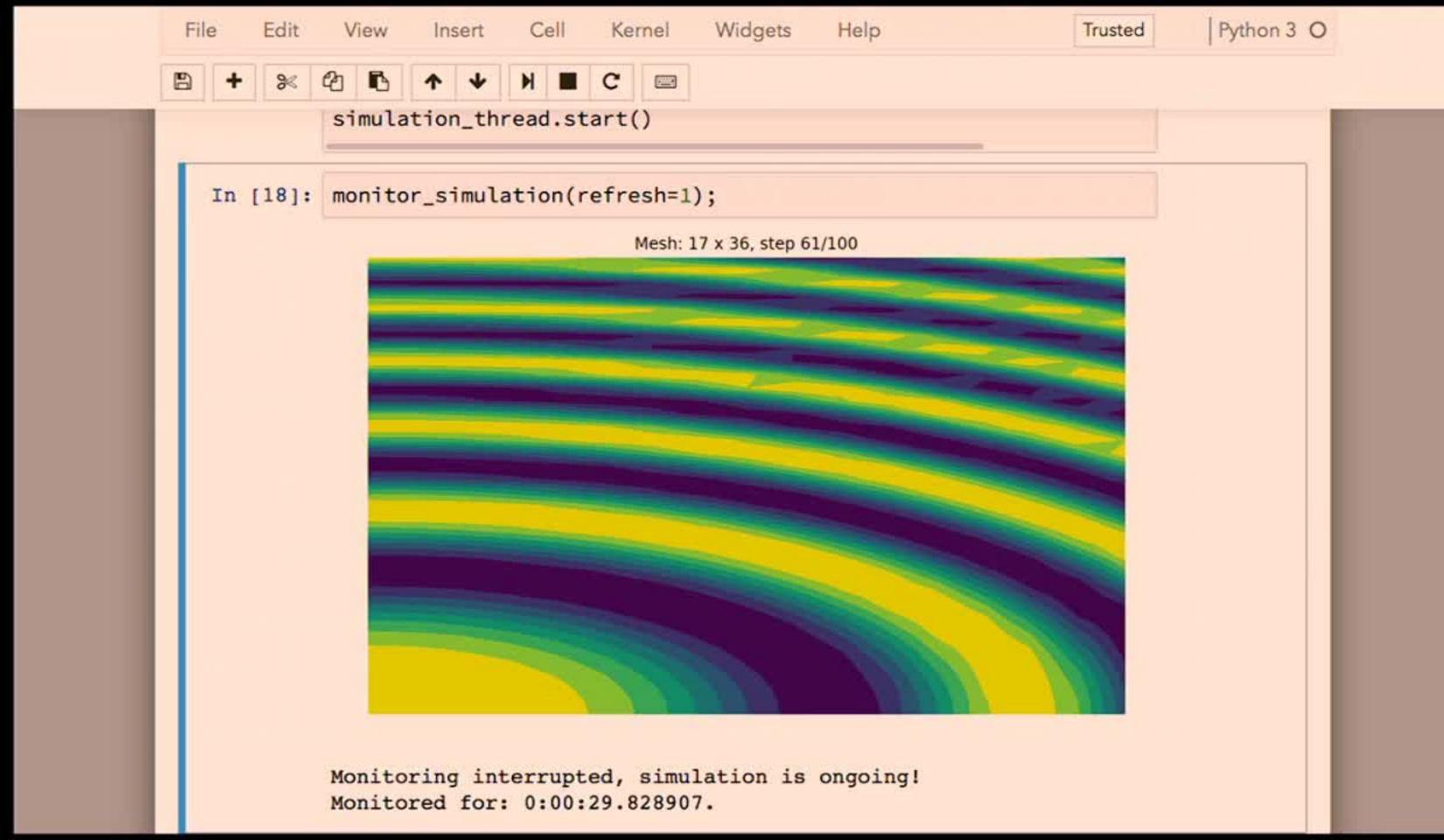
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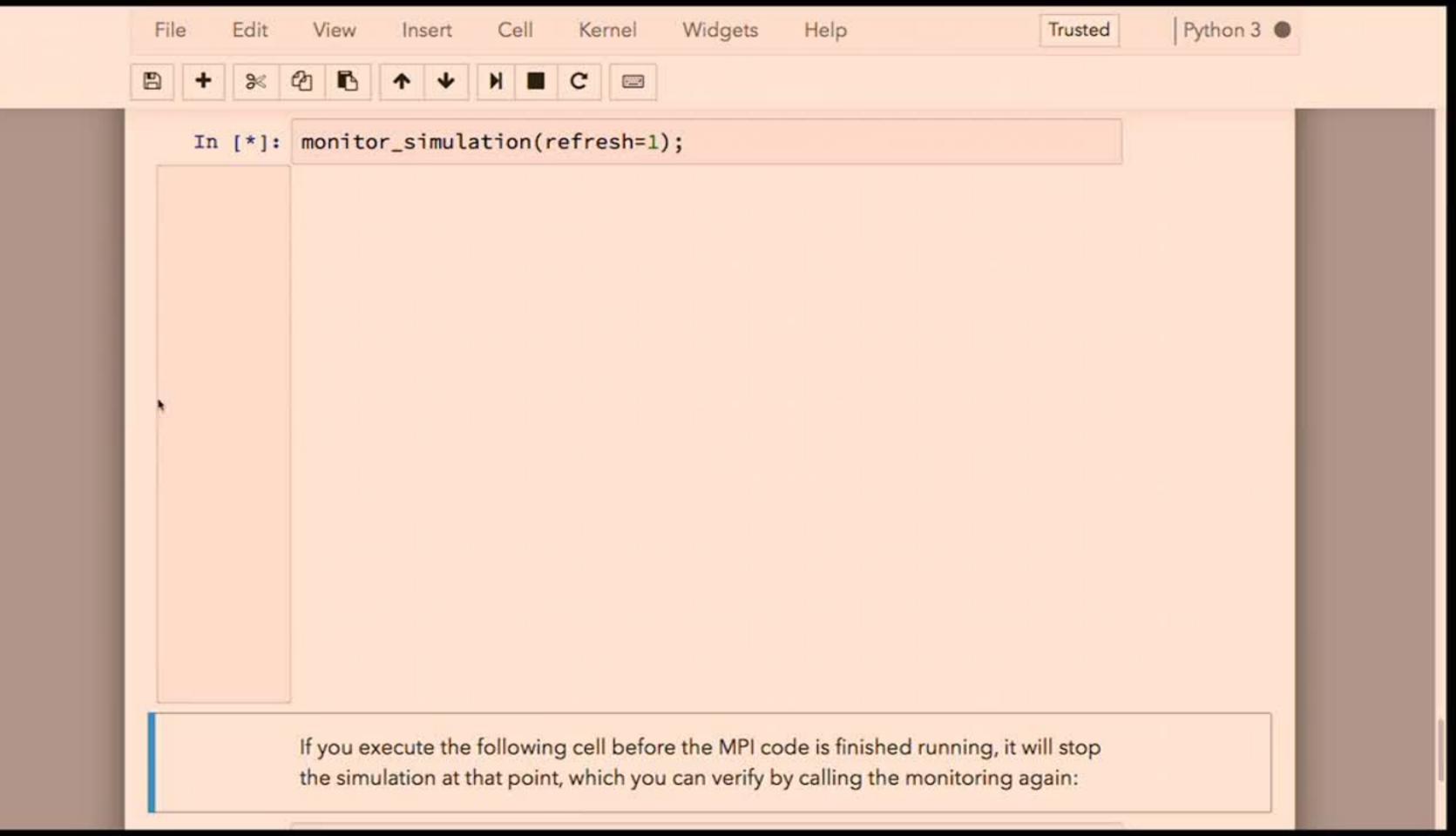
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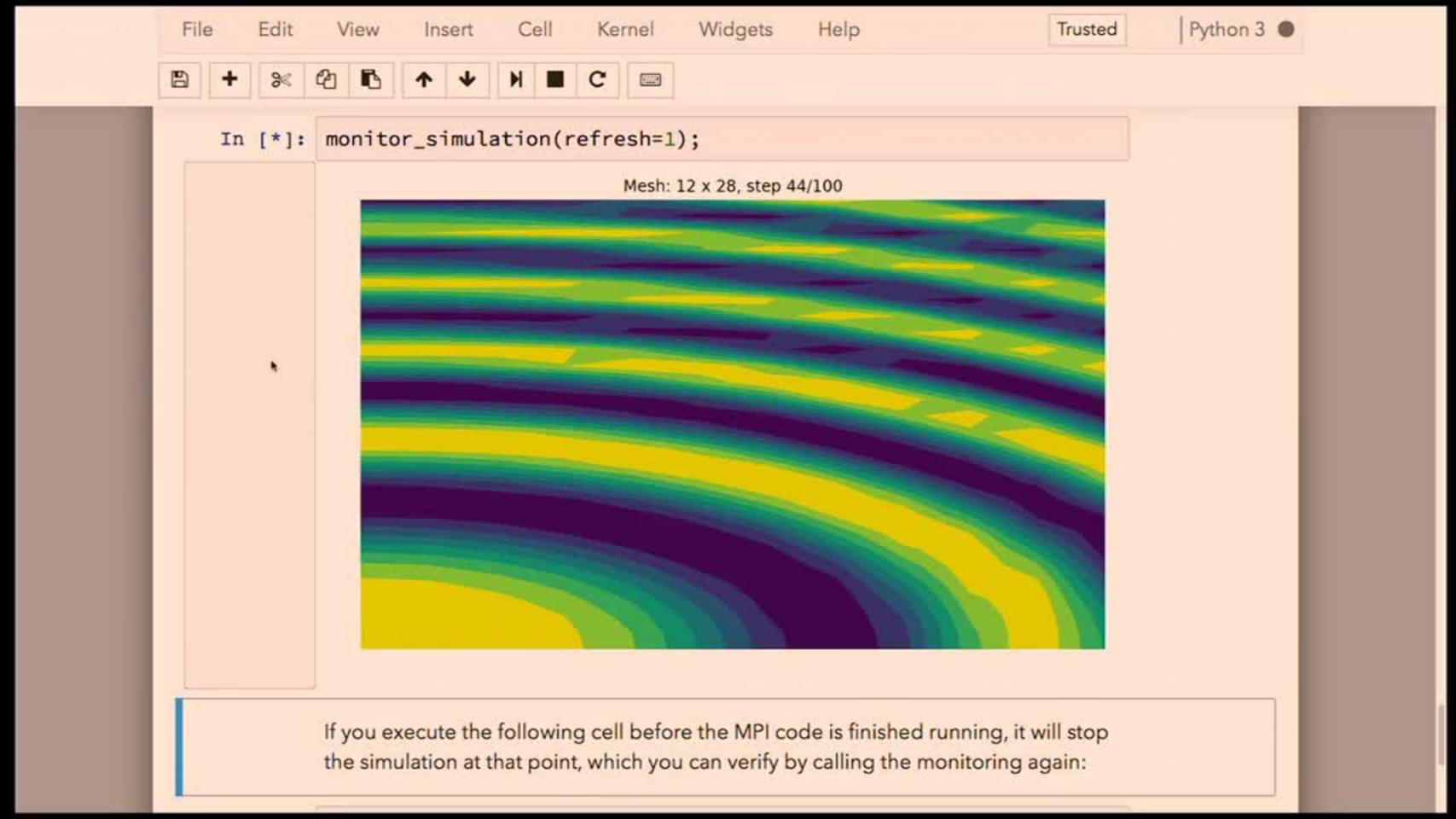
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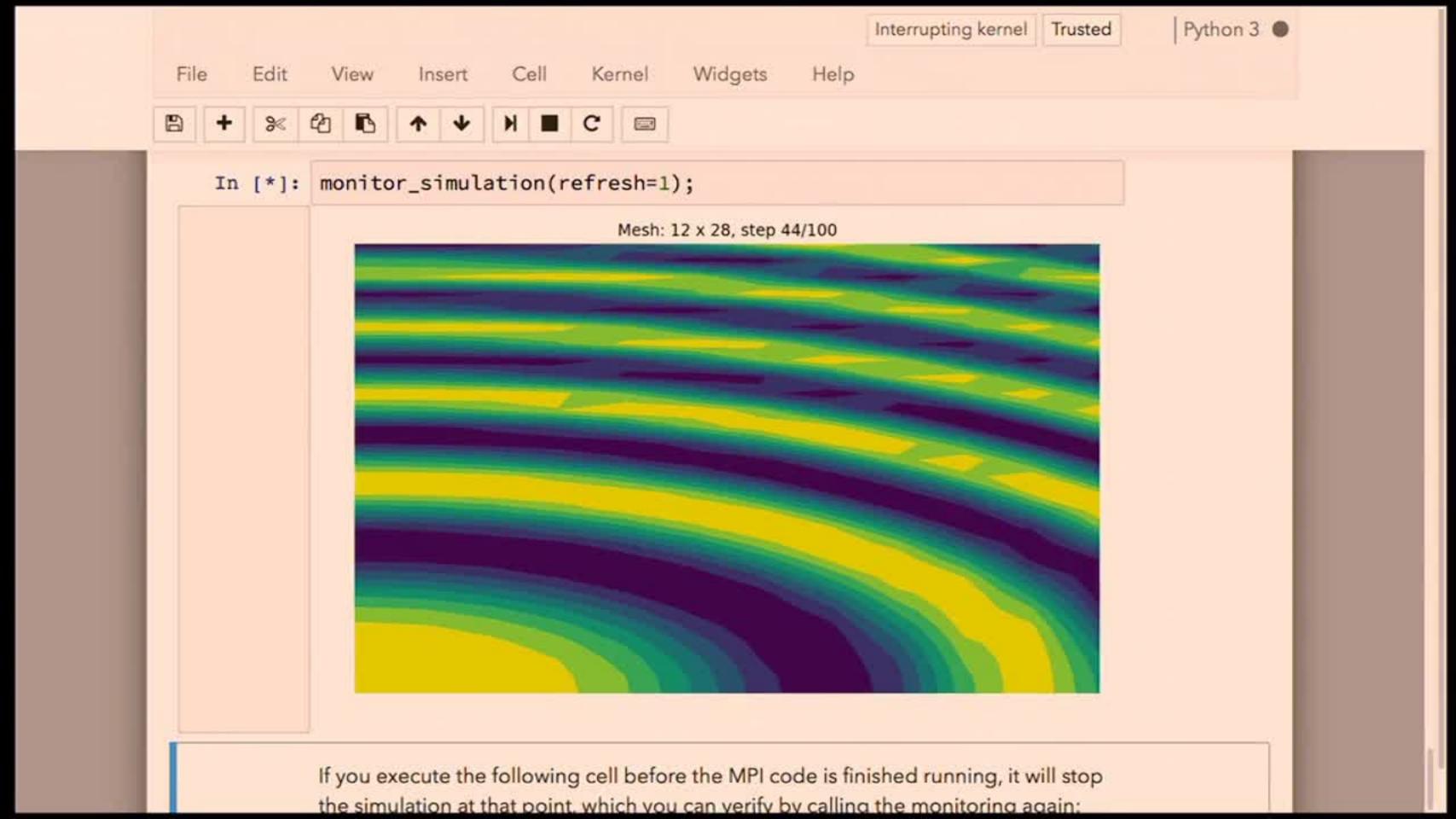






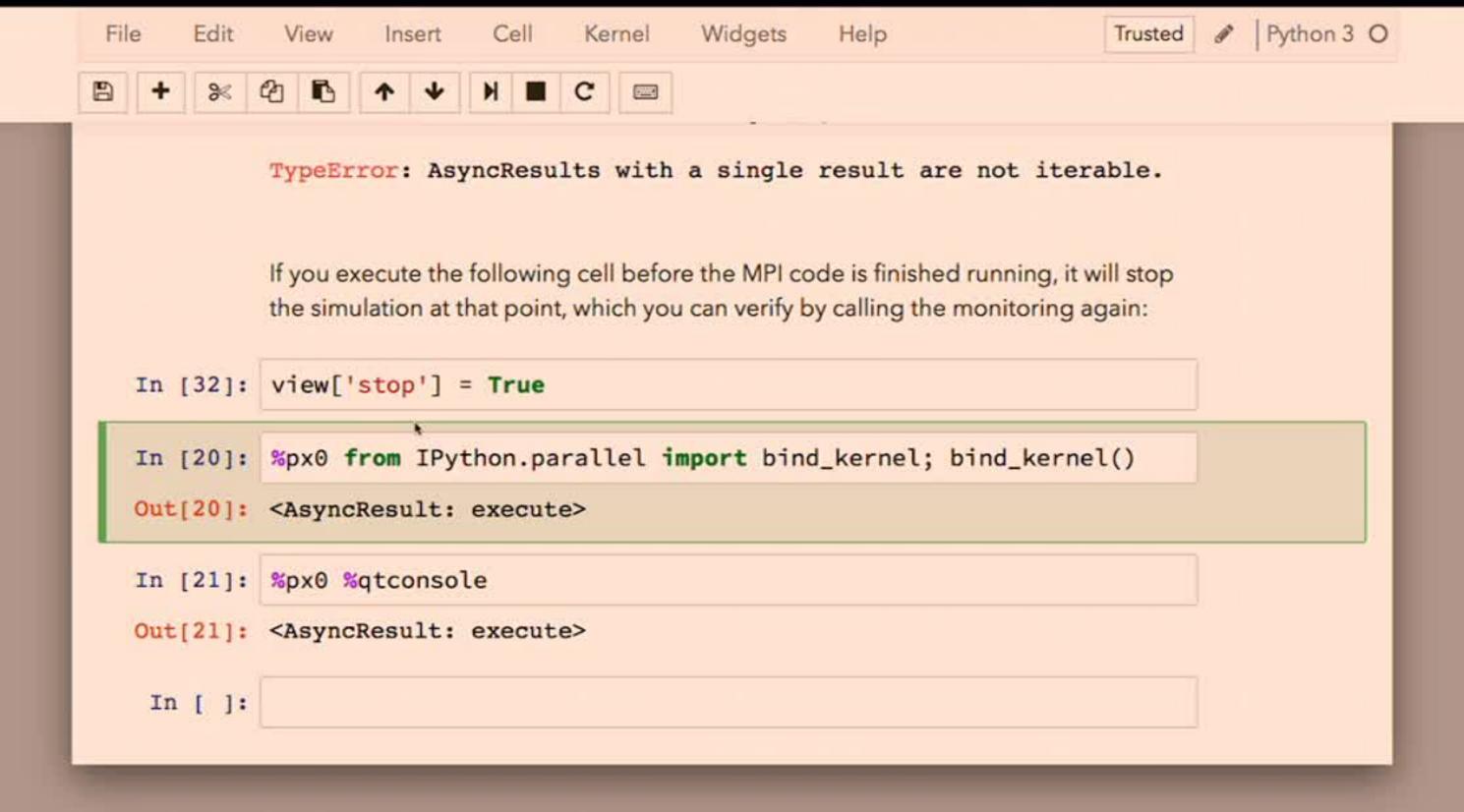


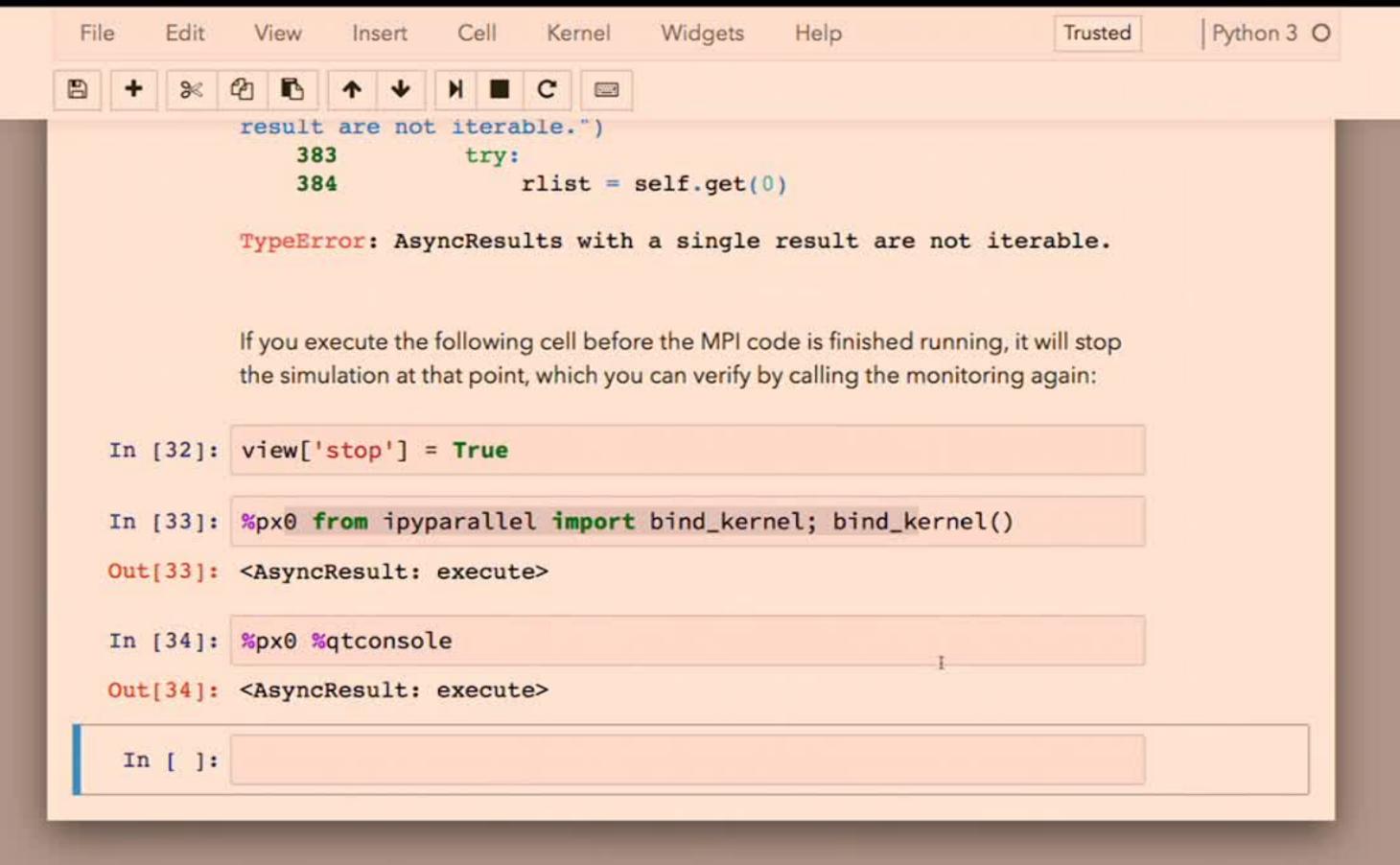


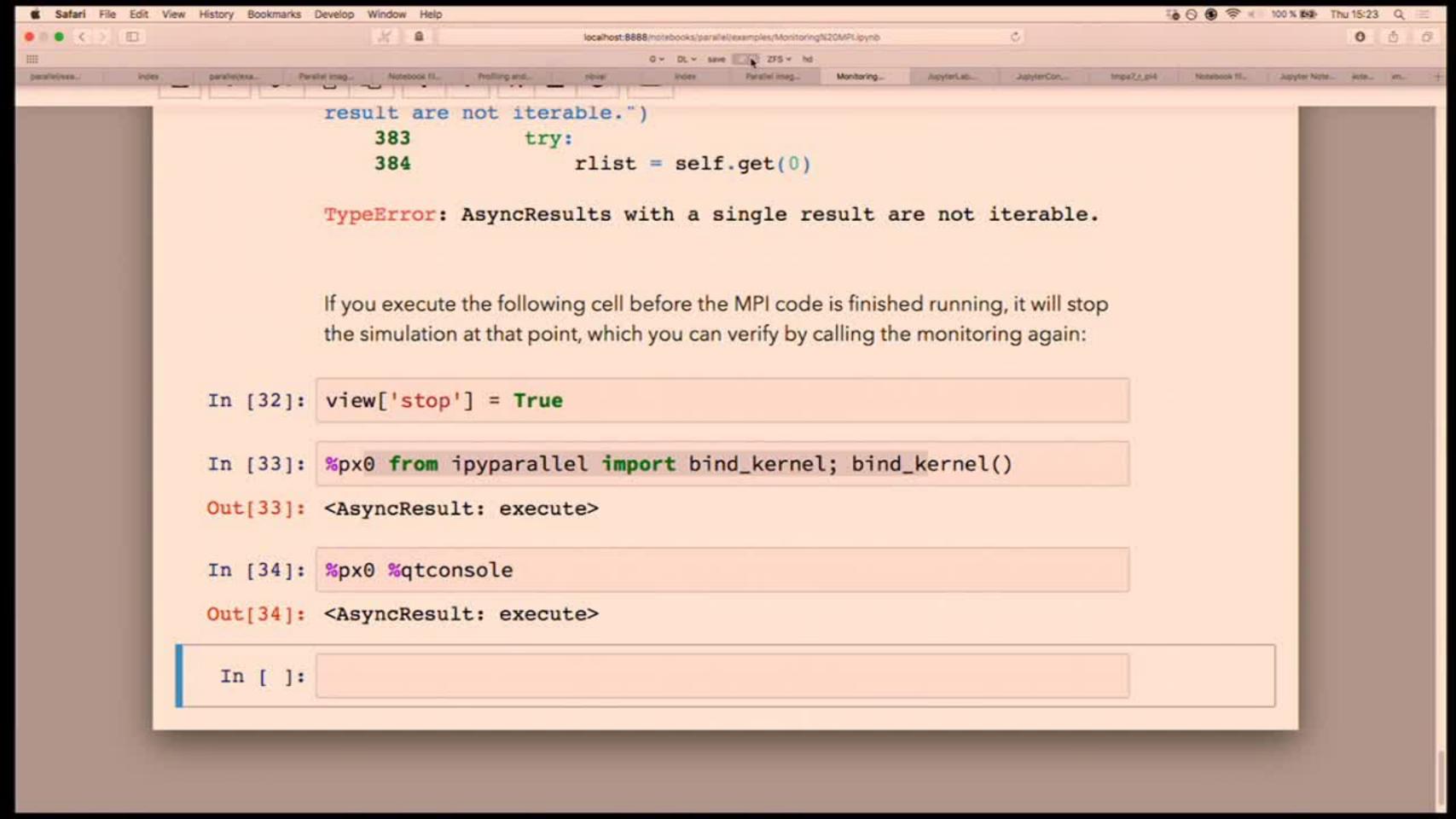


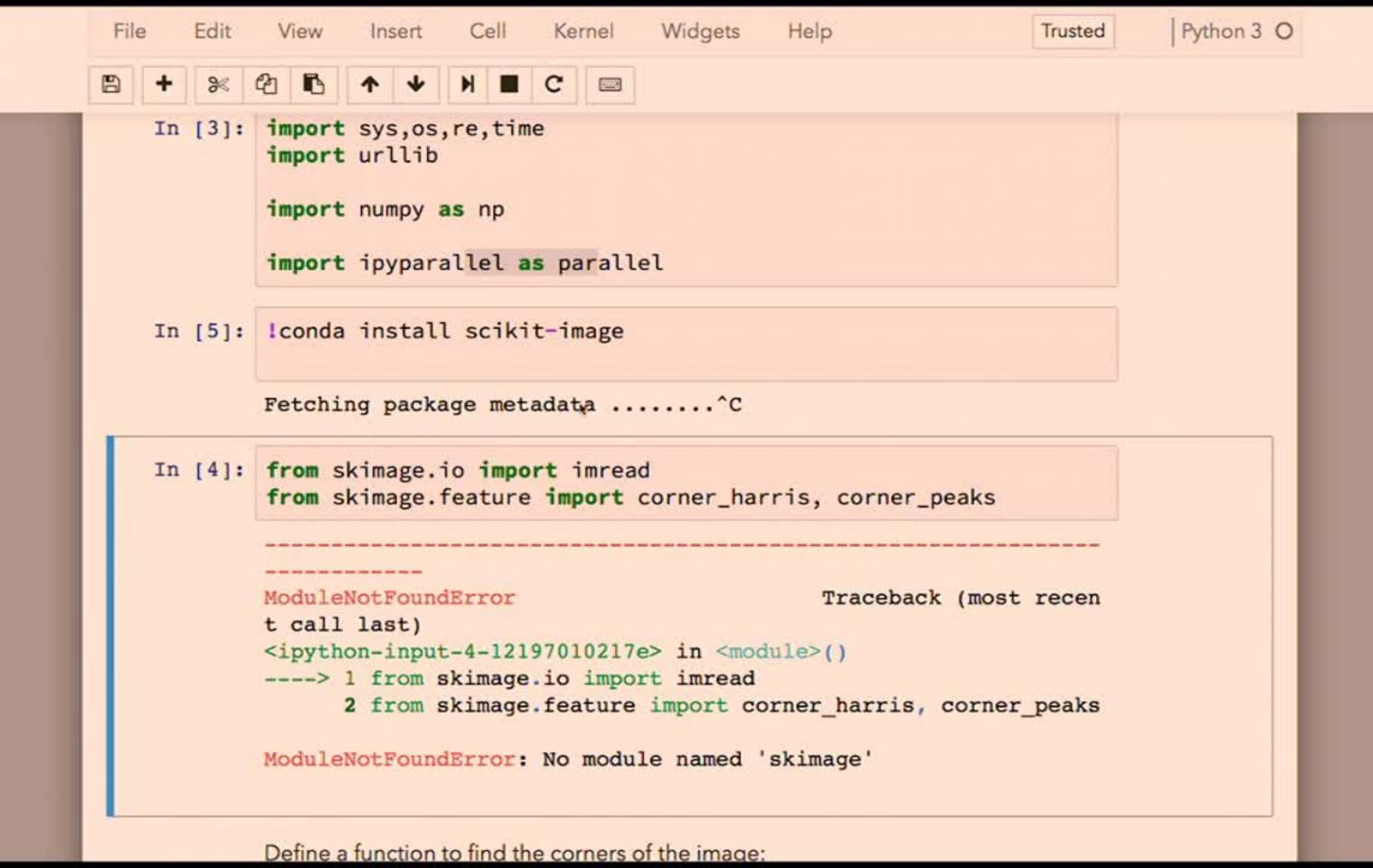


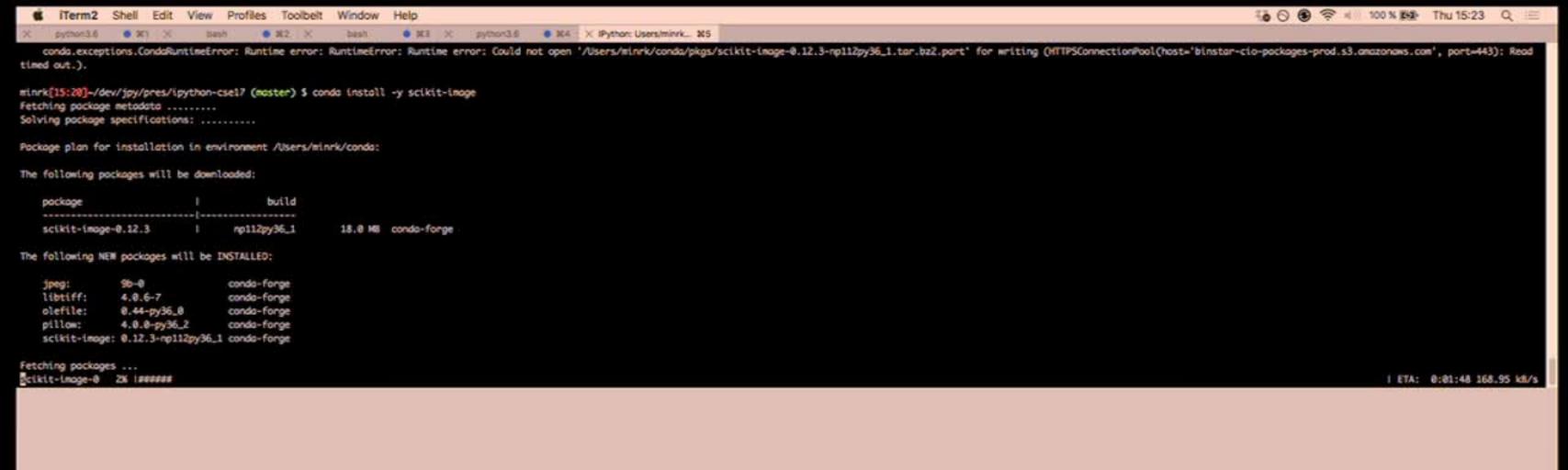
```
Traceback (most recen
TypeError
t call last)
<ipython-input-31-b619ab205d86> in <module>()
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<ipython-input-29-ae2365e1441d> in monitor simulation(refresh,
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     29
            try:
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---> 31
n place)
     32
                    plt.close('all') # prevent re-plot of old f
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<ipython-input-27-b77fff73a570> in plot current results(in plac
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     24
                return ax.figure
     25
            nx, nyt, j, nsteps = view.pull(['nx', 'nyt', 'j', '
---> 26
```











## Safari File Edit View History Bookmarks Develop Window Help

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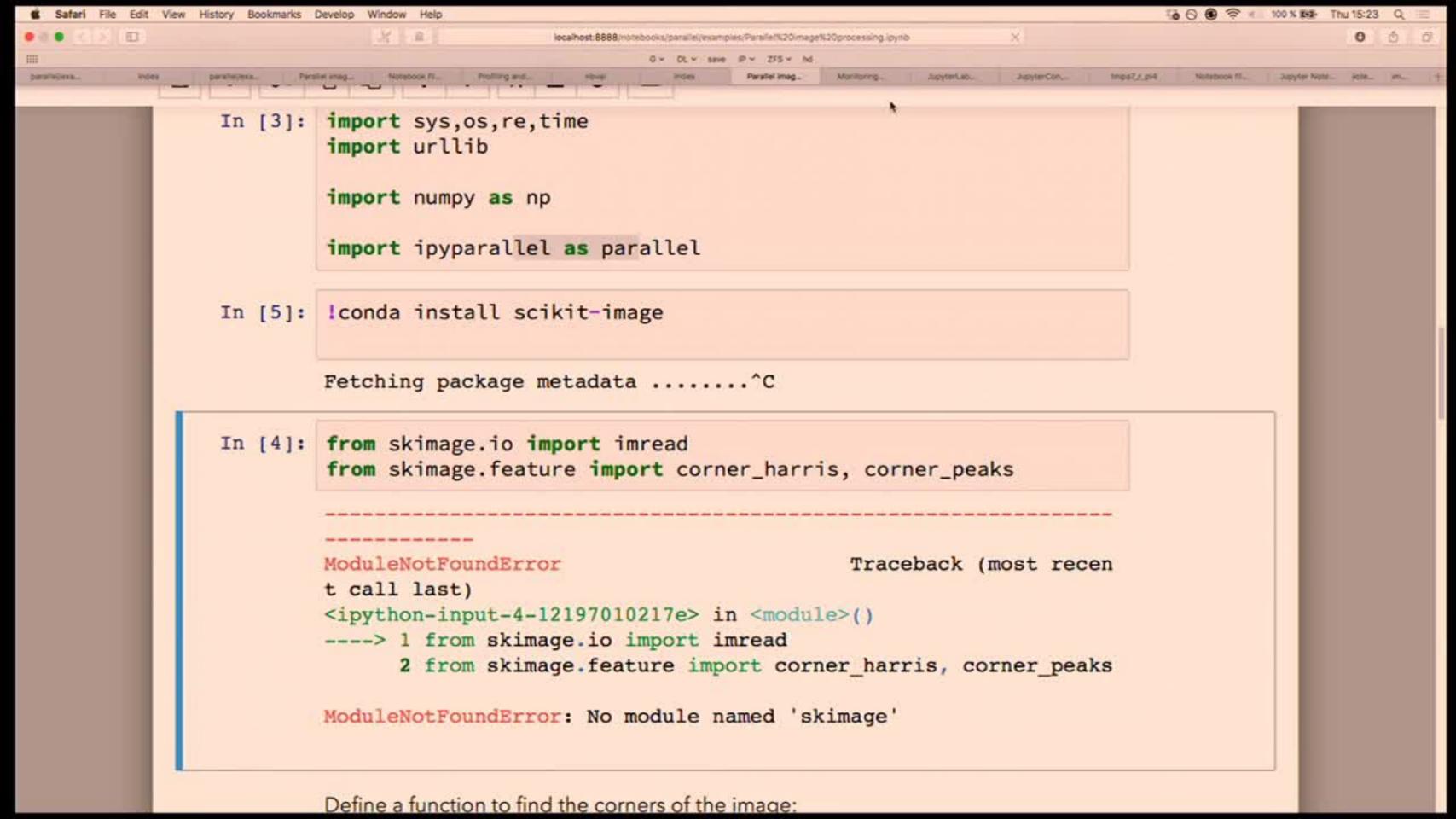
### Safari File Edit View History Bookmarks Develop Window Help

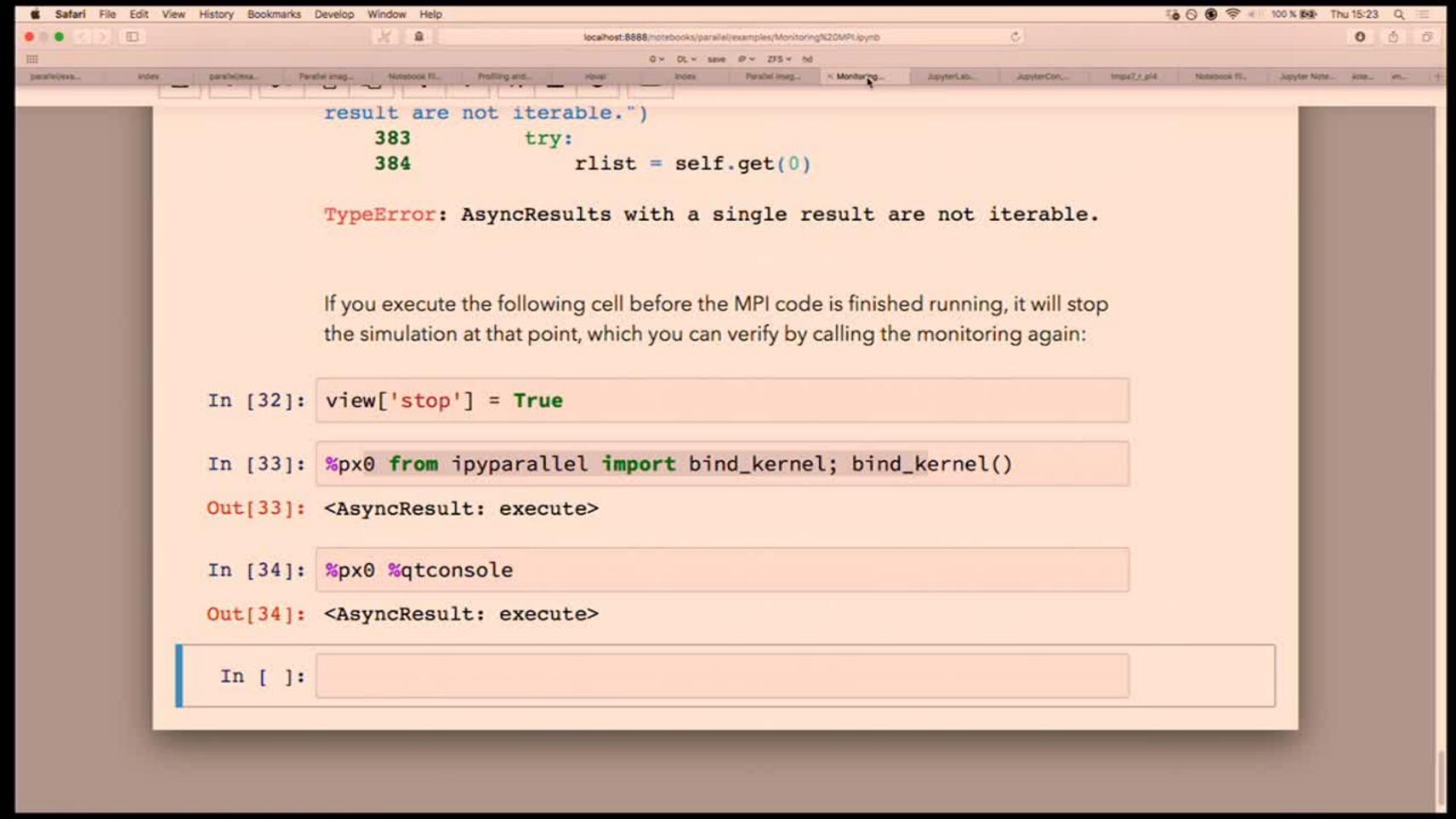
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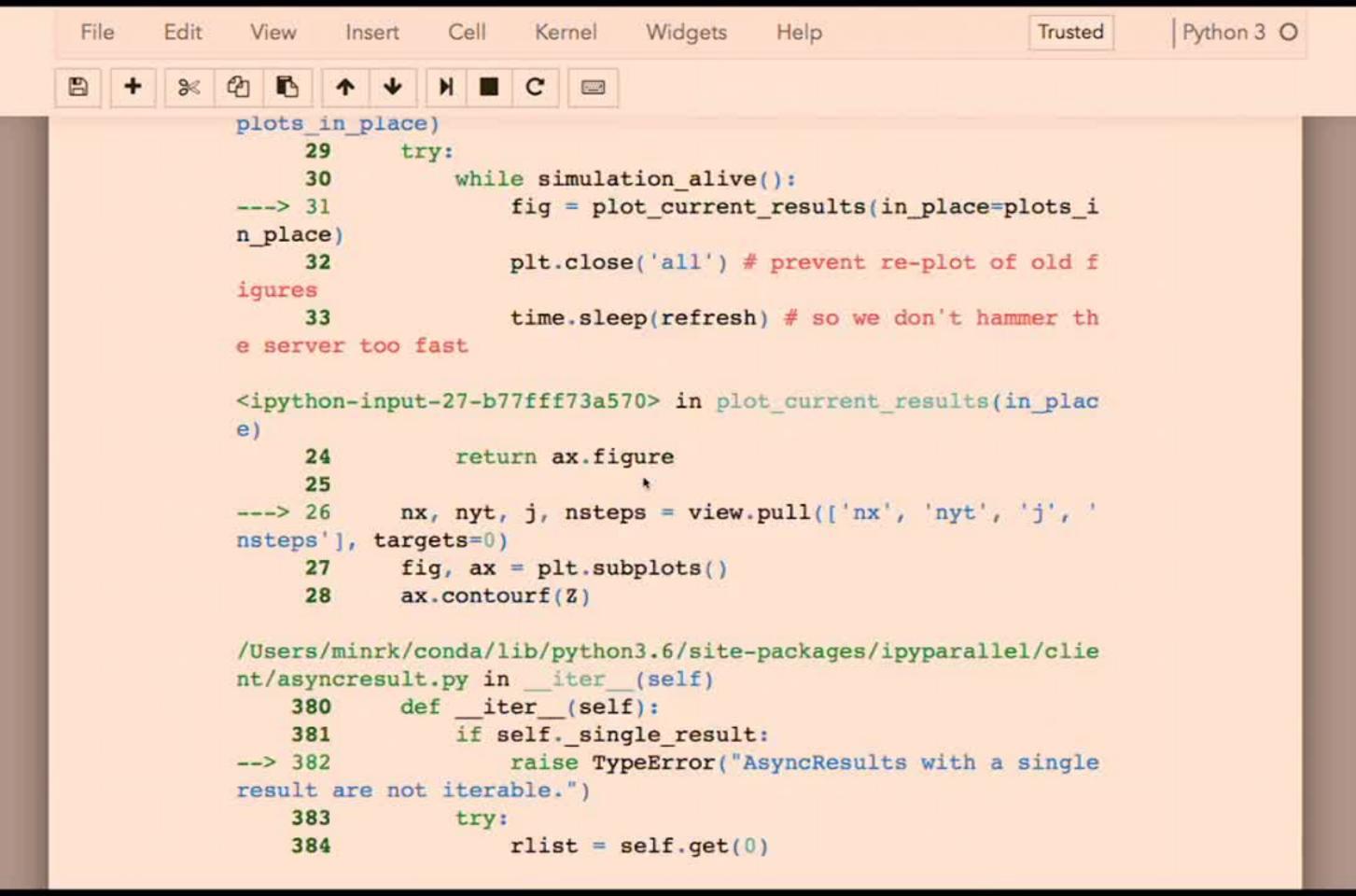
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Fetching pockages

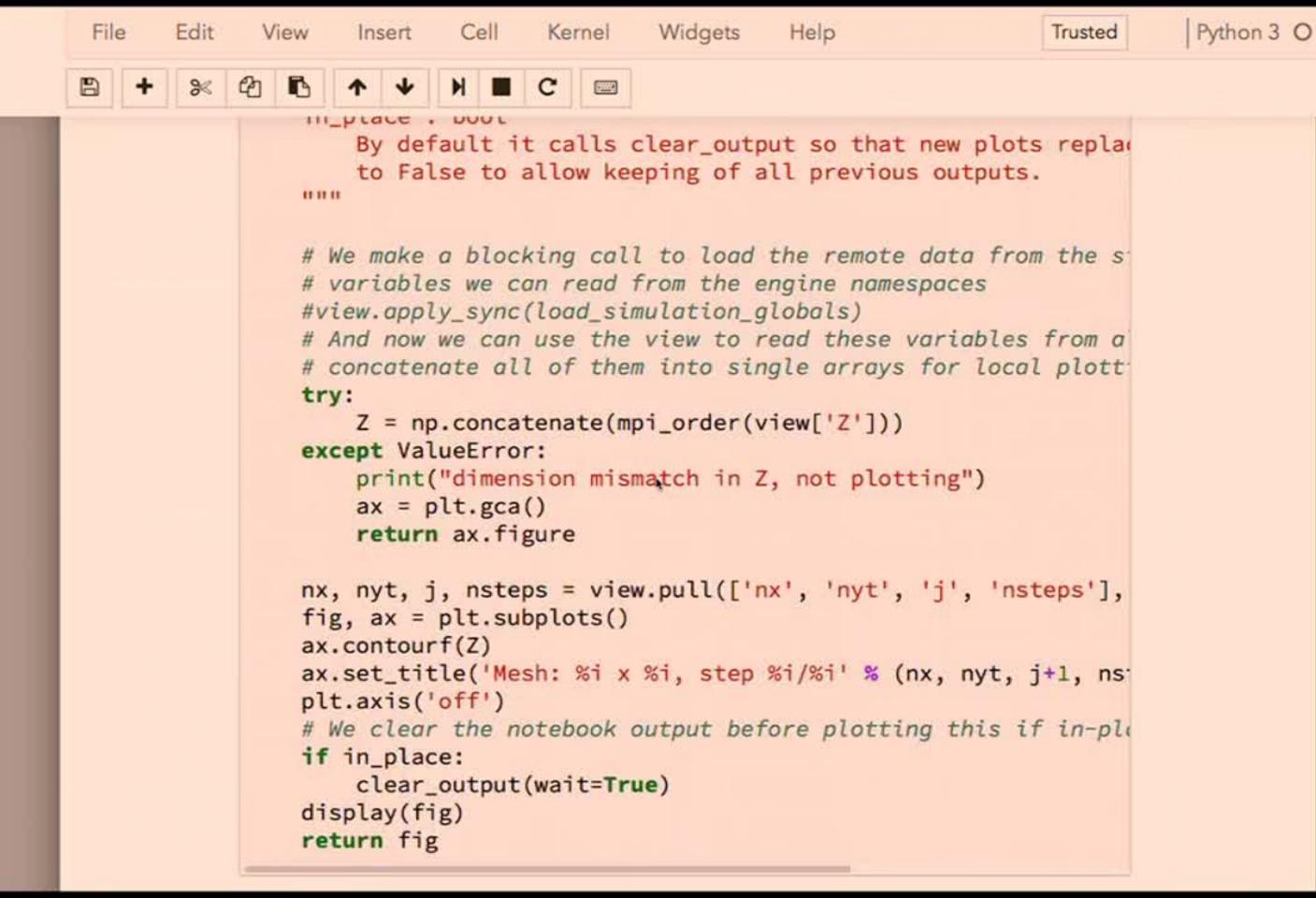
Script - Inches

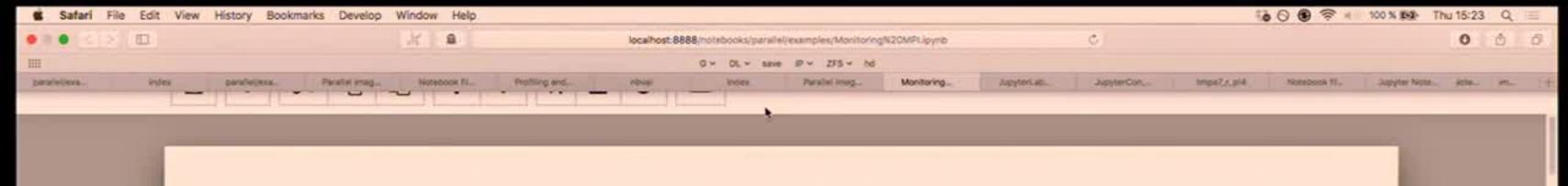






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---> 26
nsteps'], targets=0)
          fig. ax = nlt.subplots()
```



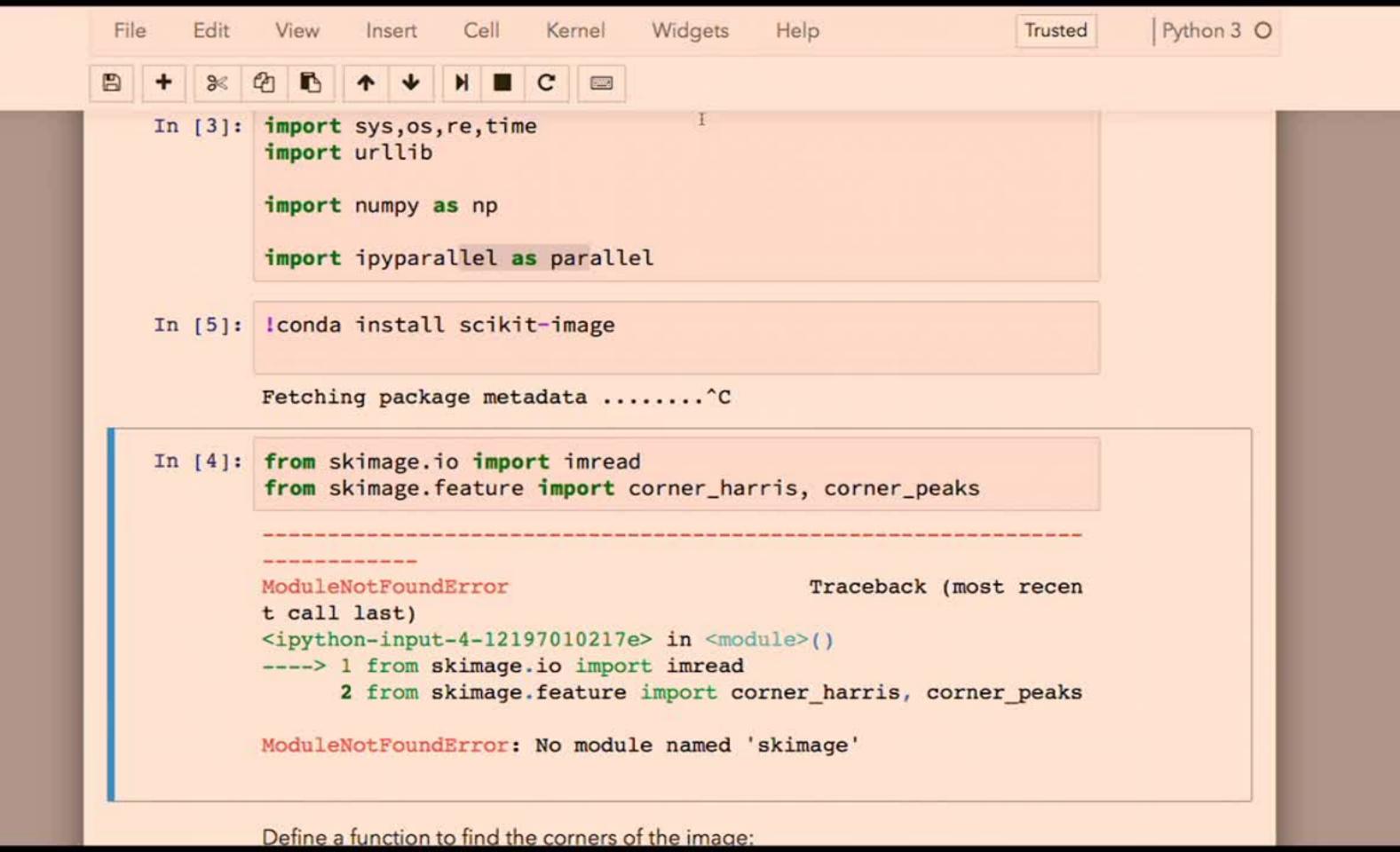


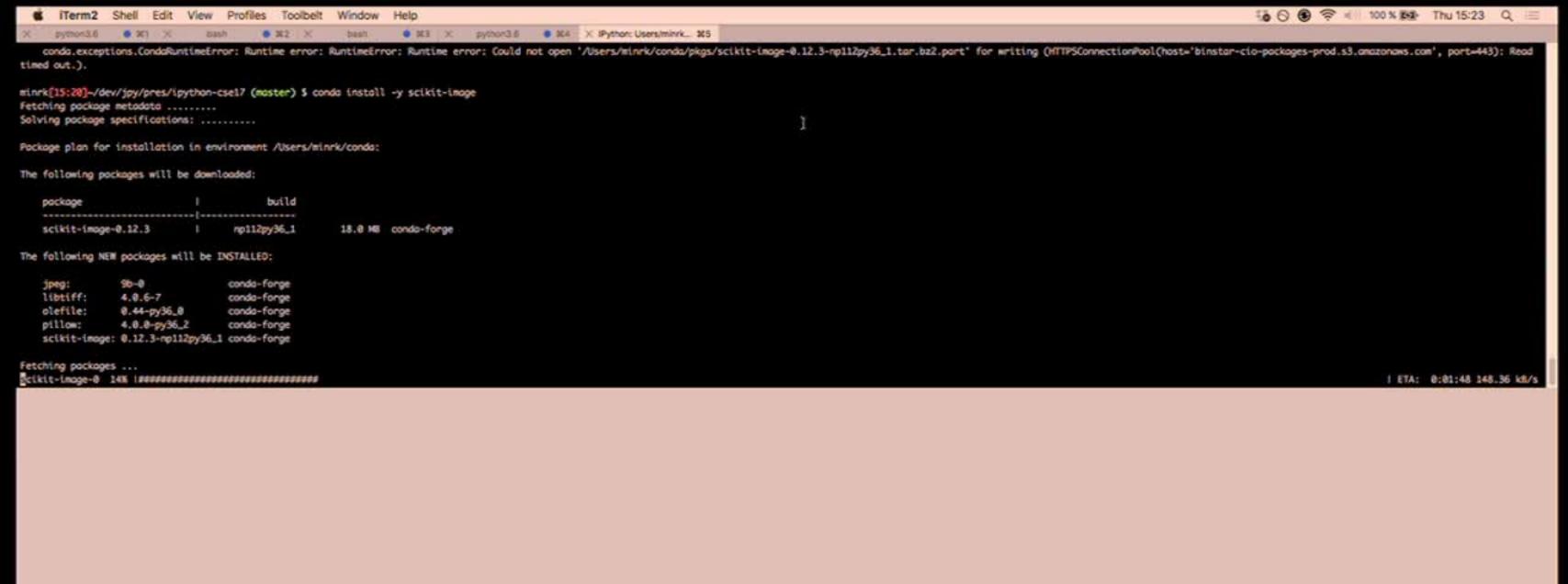
## Interactive monitoring of a parallel MPI simulation with the IPython Notebook

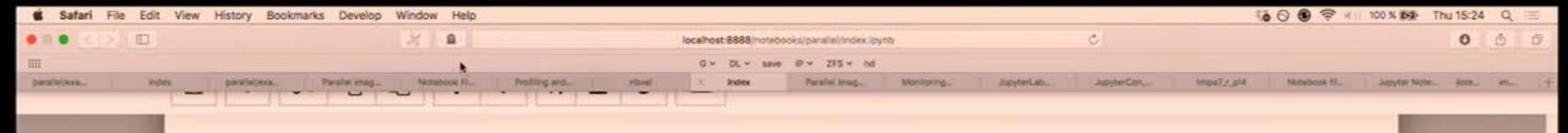
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## Interactive (parallel) Python

## Installation and dependencies

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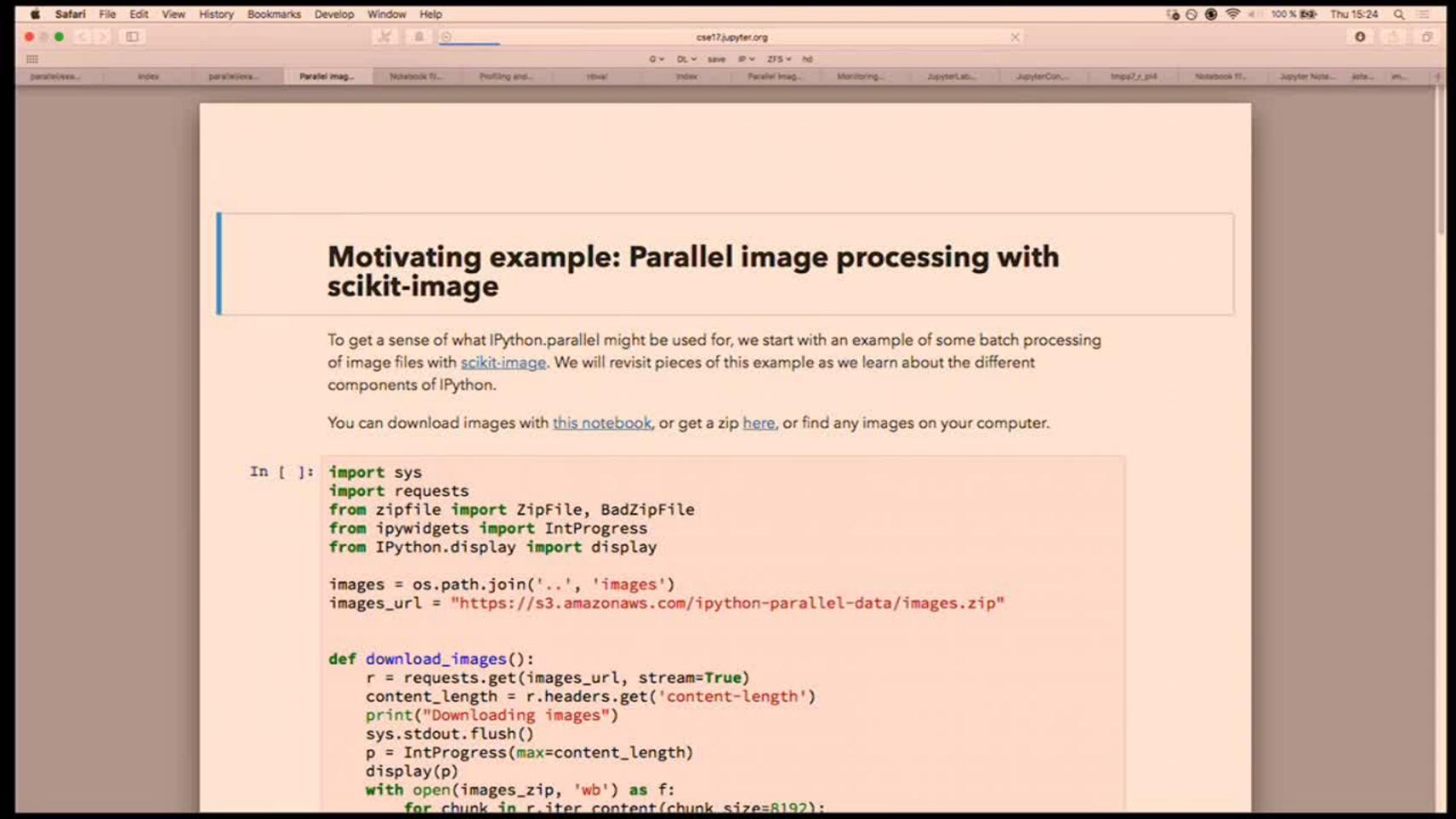
pip install ipyparallel

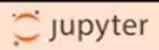
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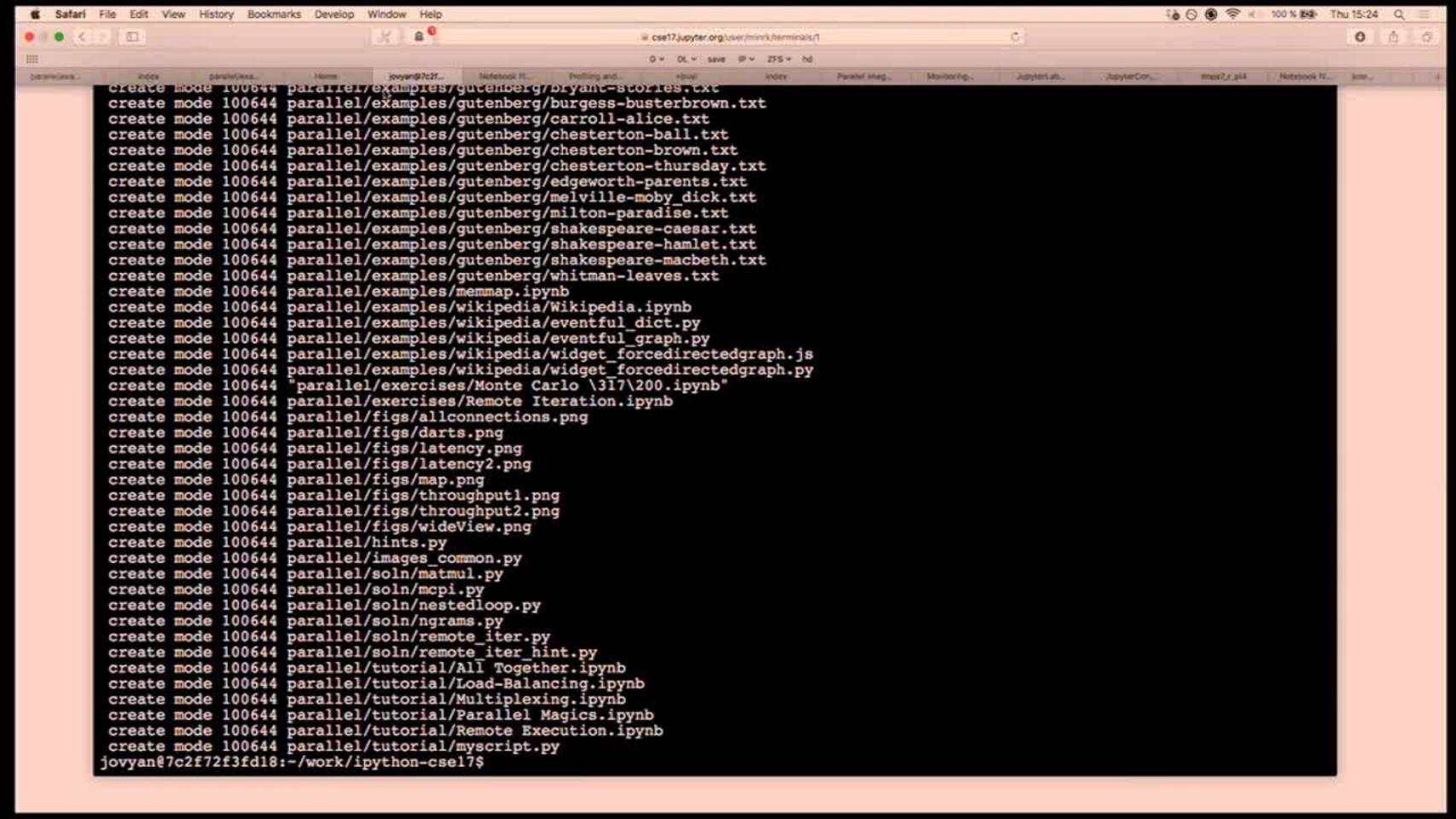
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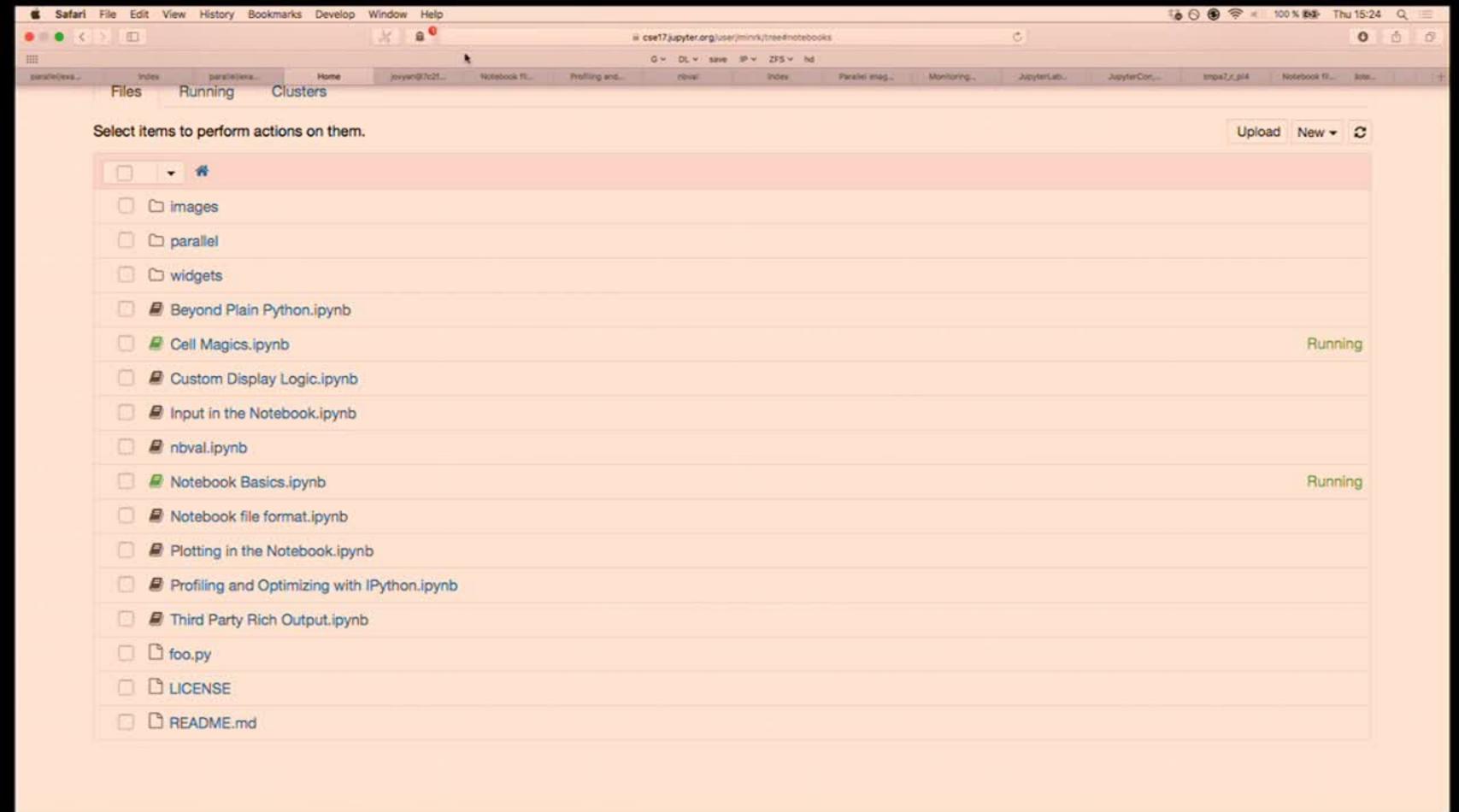
ipython ipyparallel numpy matplotlib networkx scikit-image requests beautifulsoup mpi4py

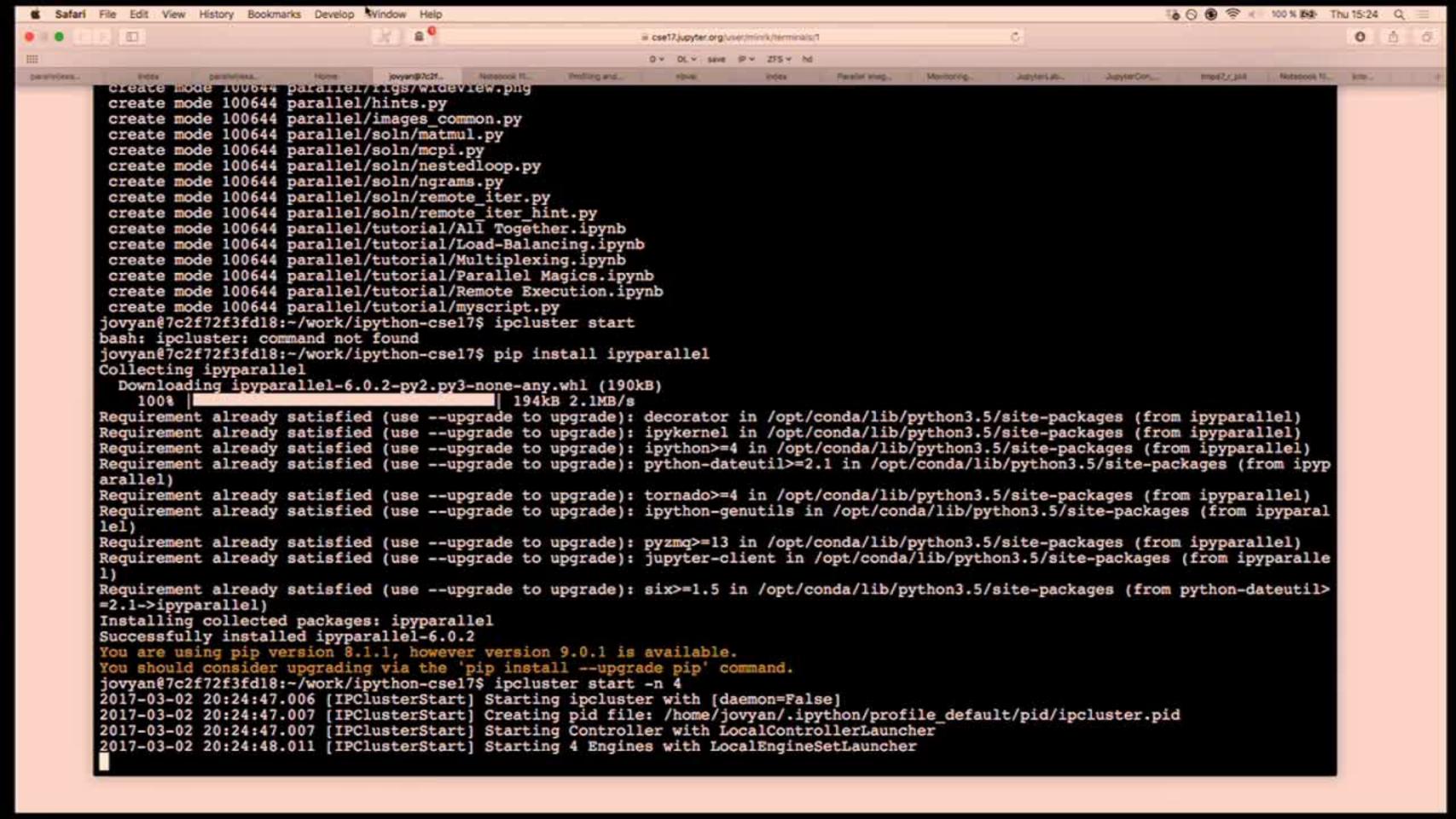


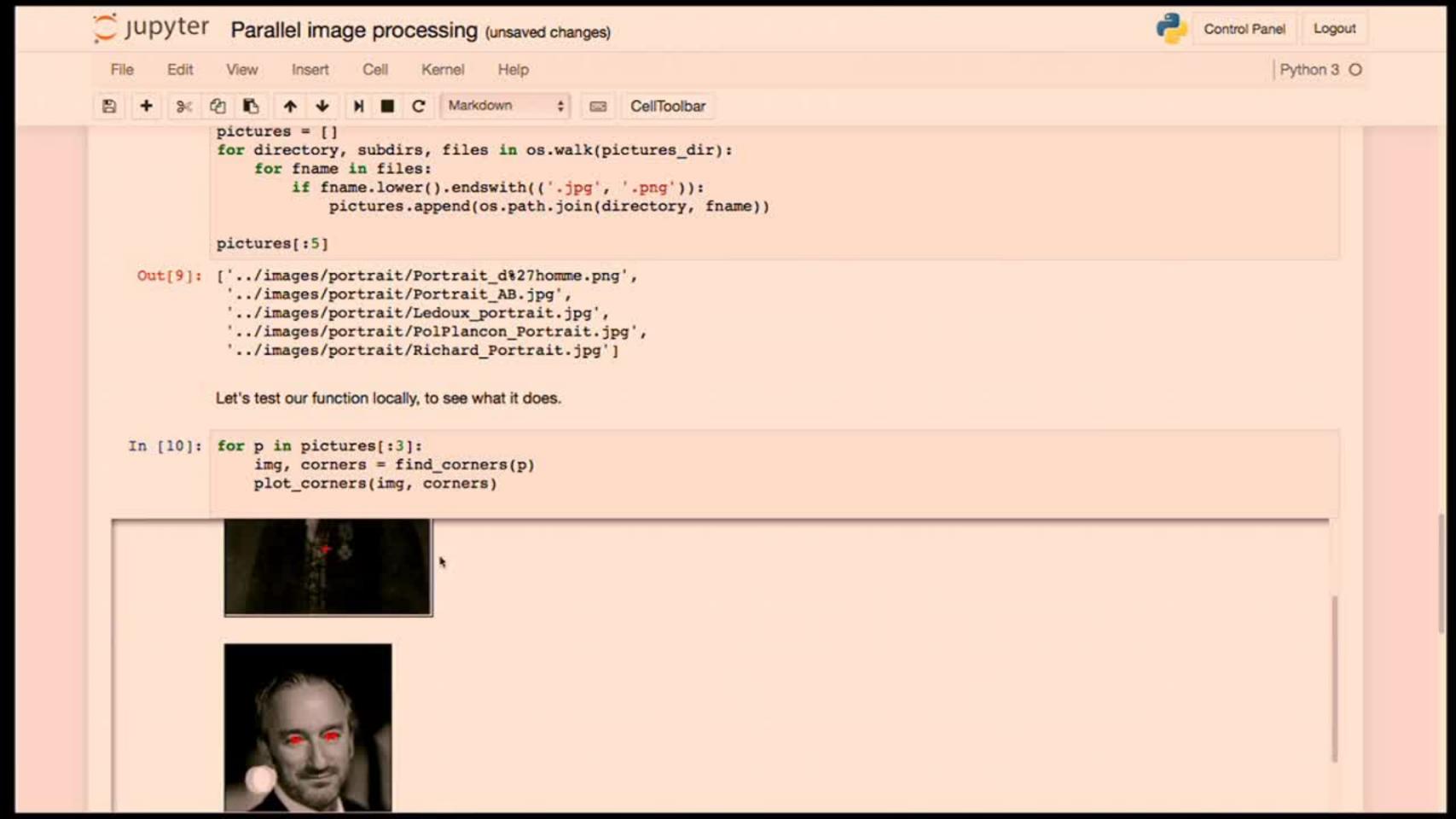


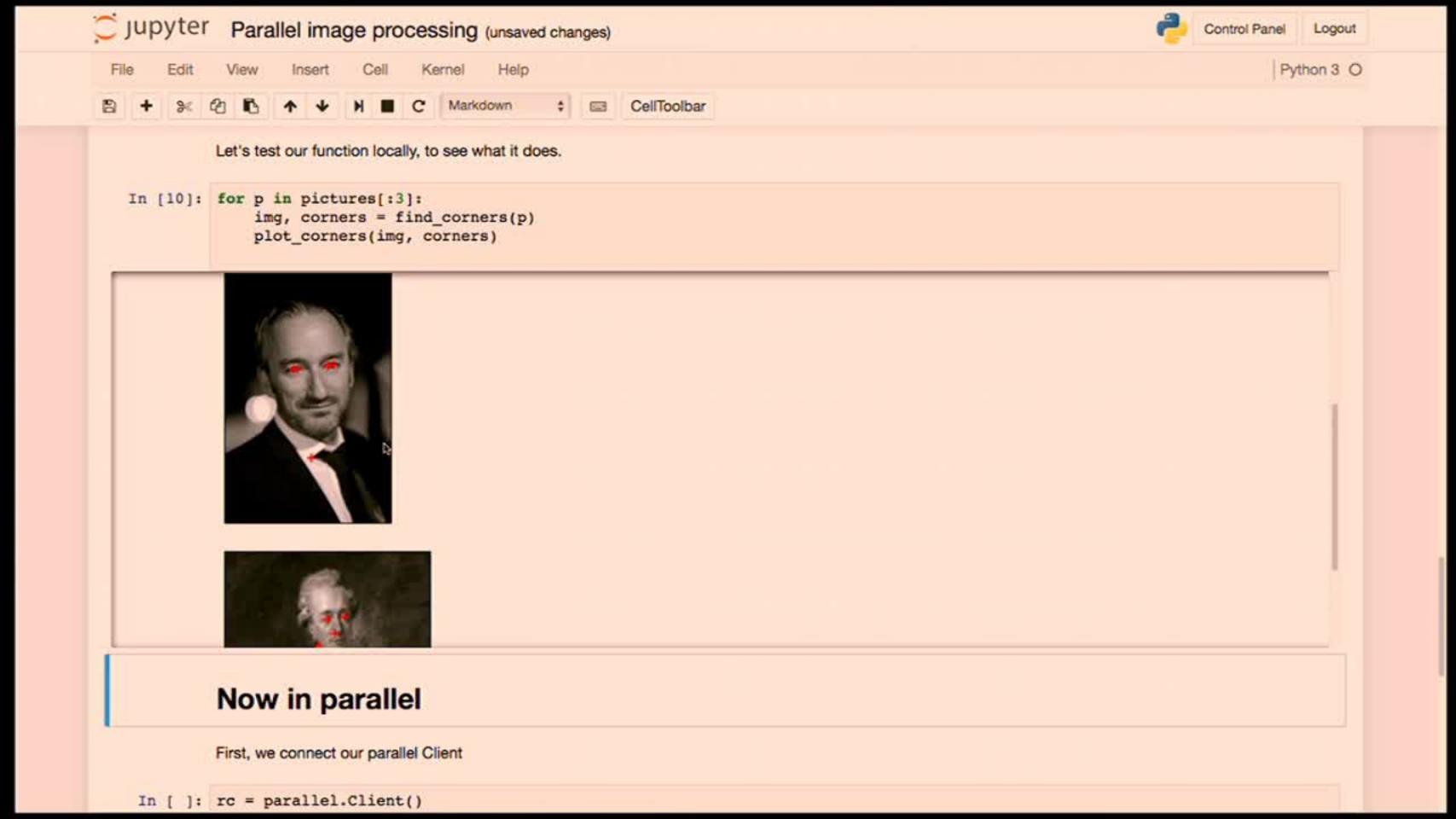
Files	Files Running Clusters									
Select items to perform actions on them.					Upload	New →	2			
10	+ #									
0	☐ images									
	□ widgets									
10	Beyond Plai	in Python.ipynb								
	Cell Magics	i.ipynb							Runn	ing
0	Custom Dis	splay Logic.ipynb								
0	■ Input in the	Notebook.ipynb								
0	■ Notebook B	Basics.ipynb							Runn	ing
0	■ Third Party	Rich Output.ipynb								
0	foo.py									
0	LICENSE									
0	README.m	d								





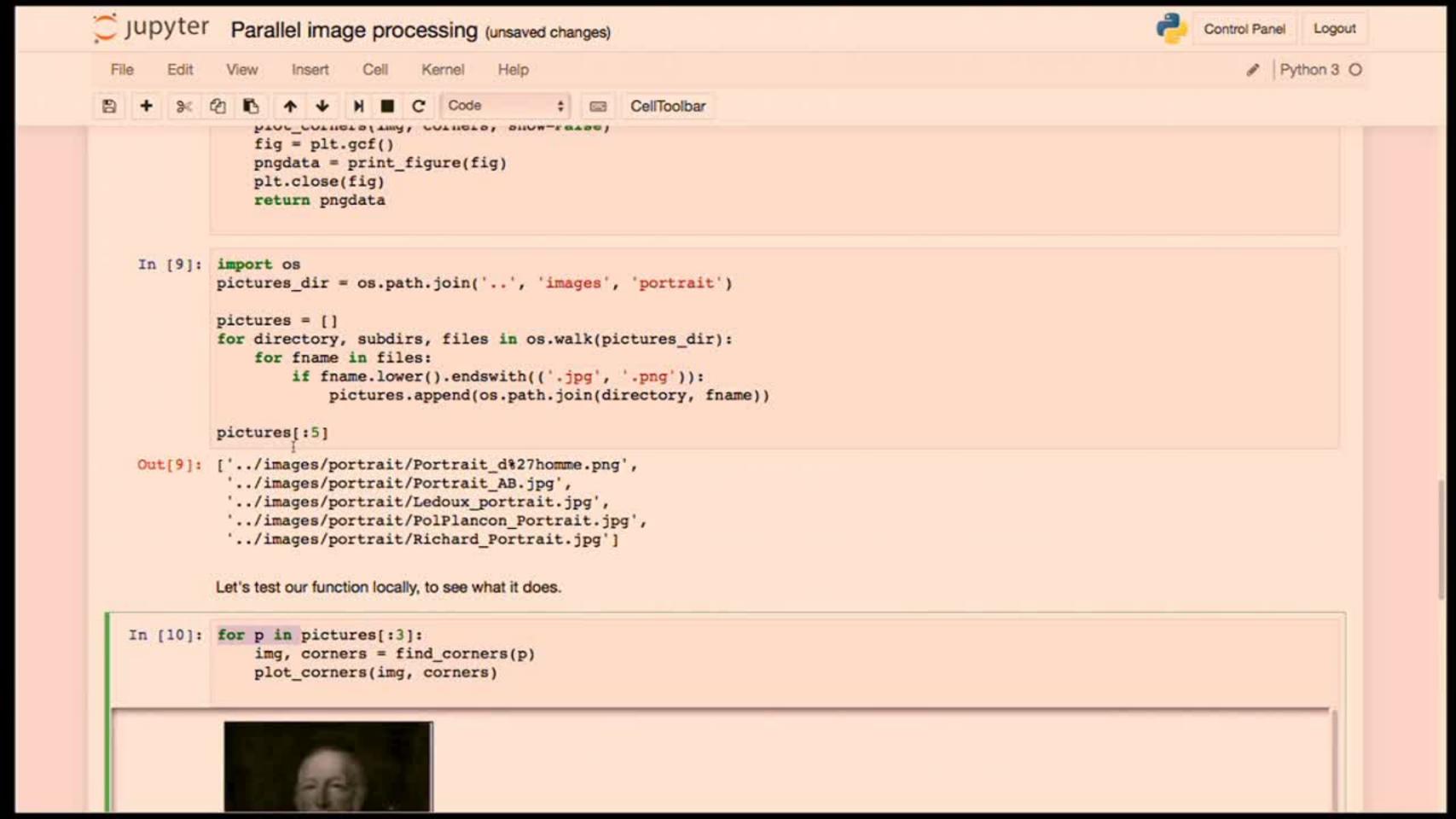


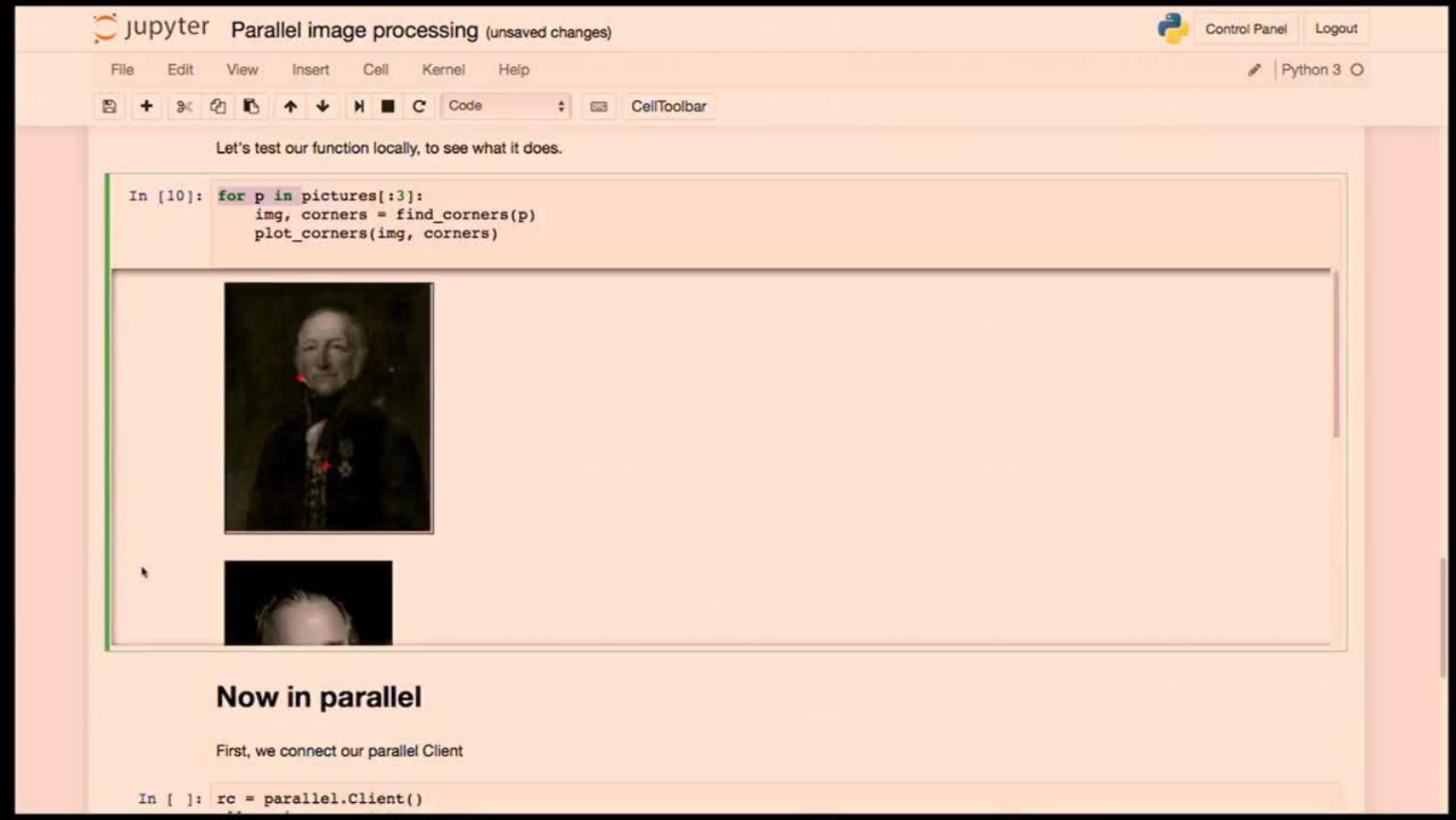




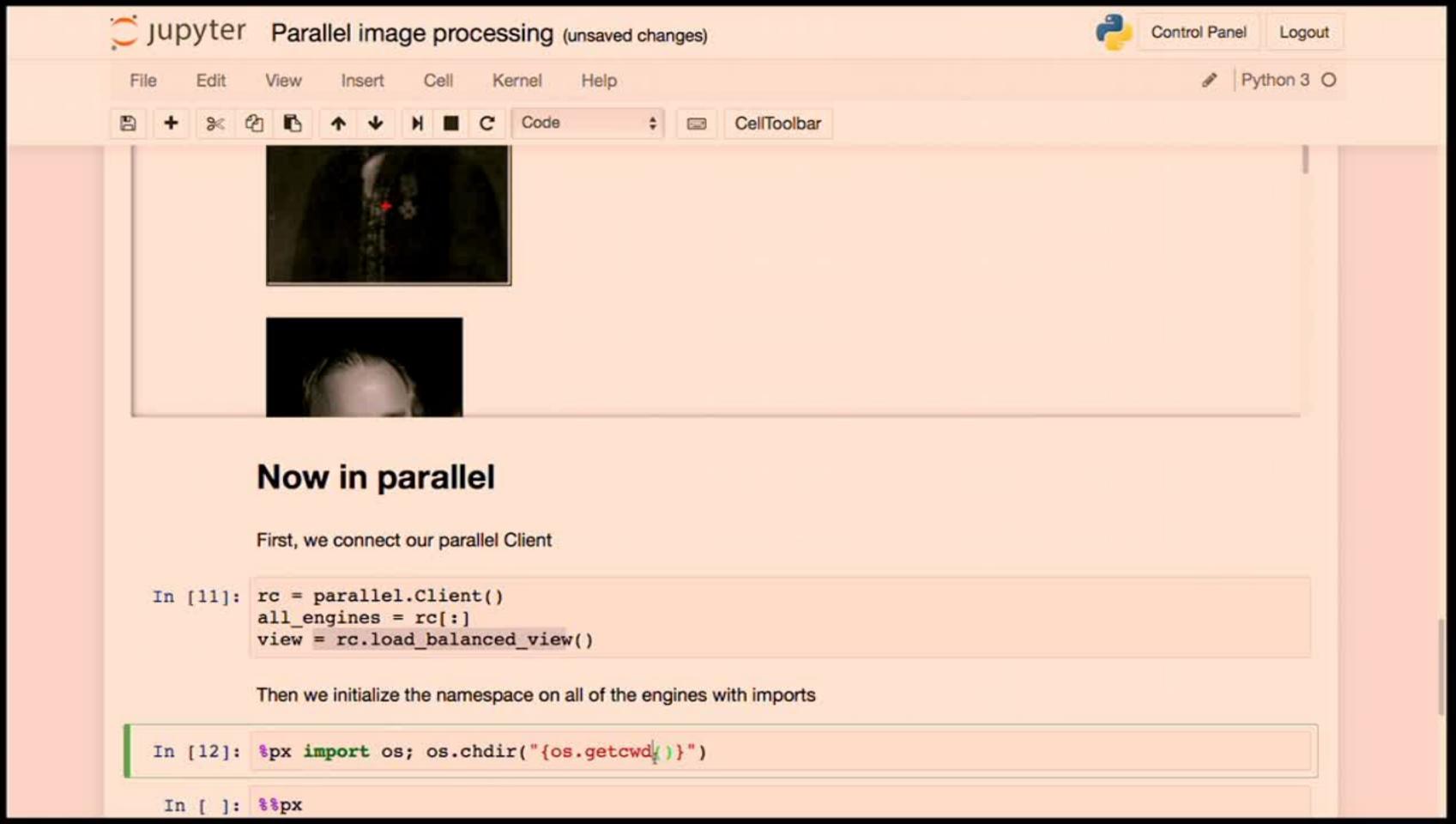


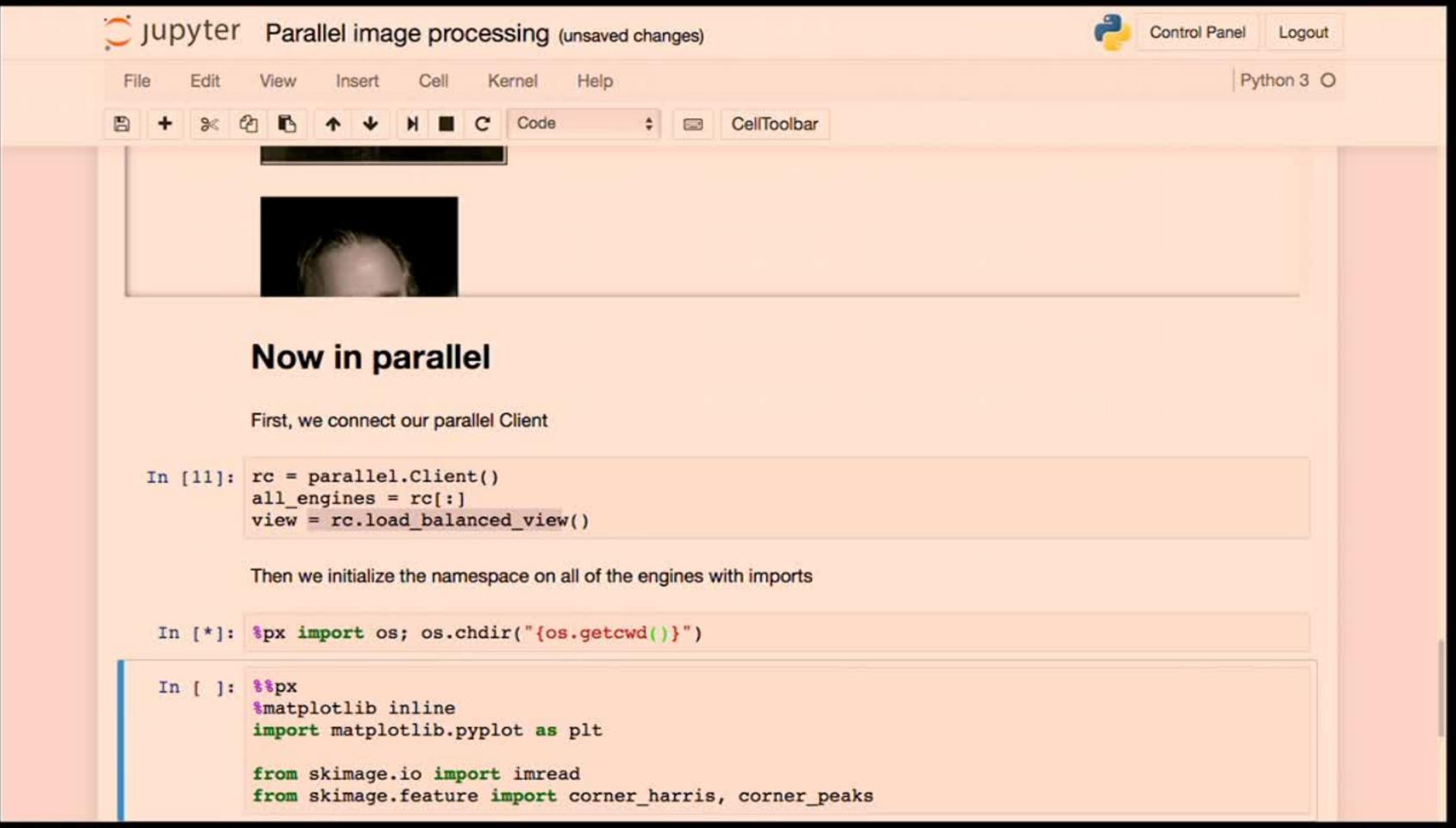






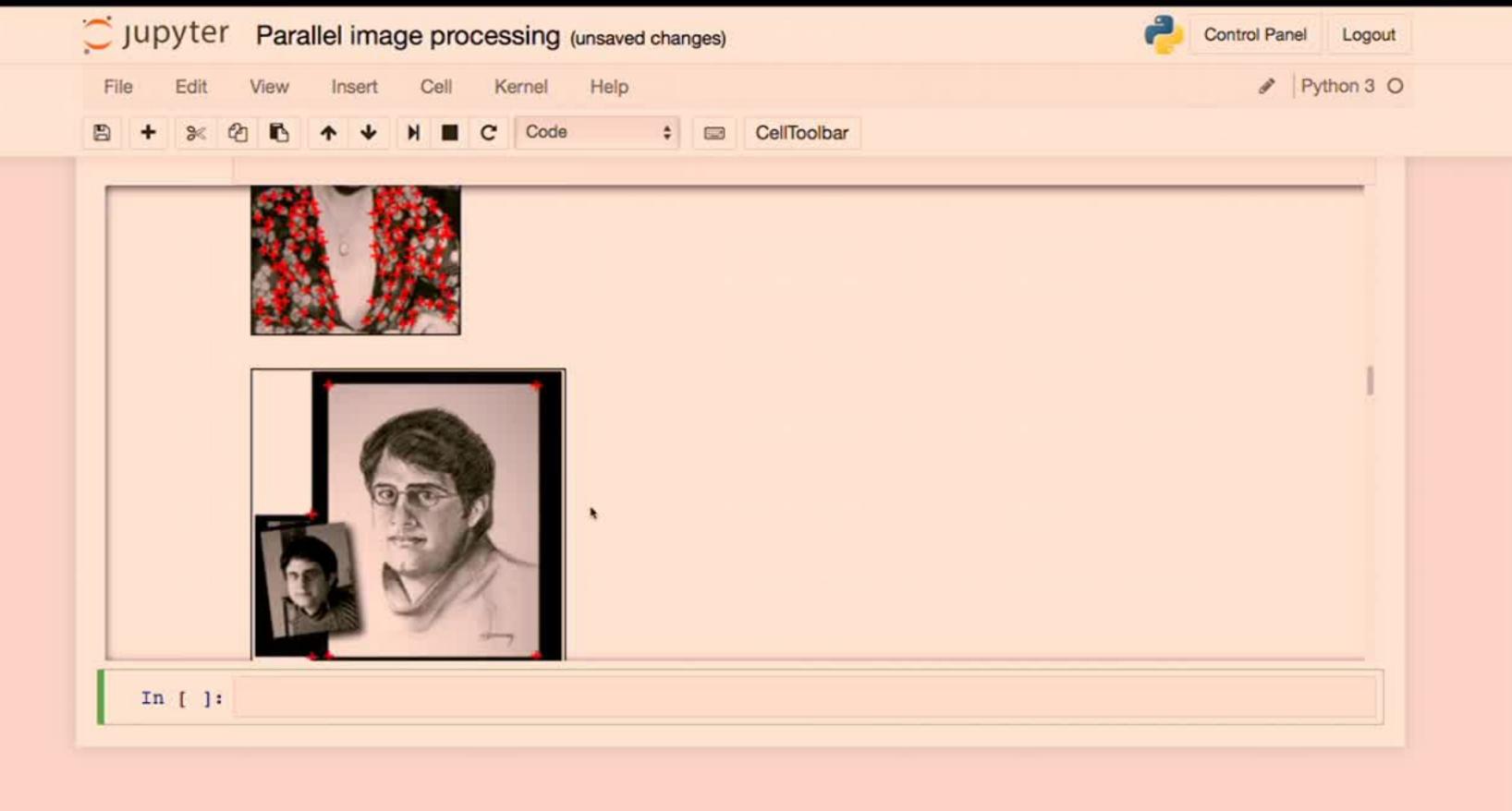
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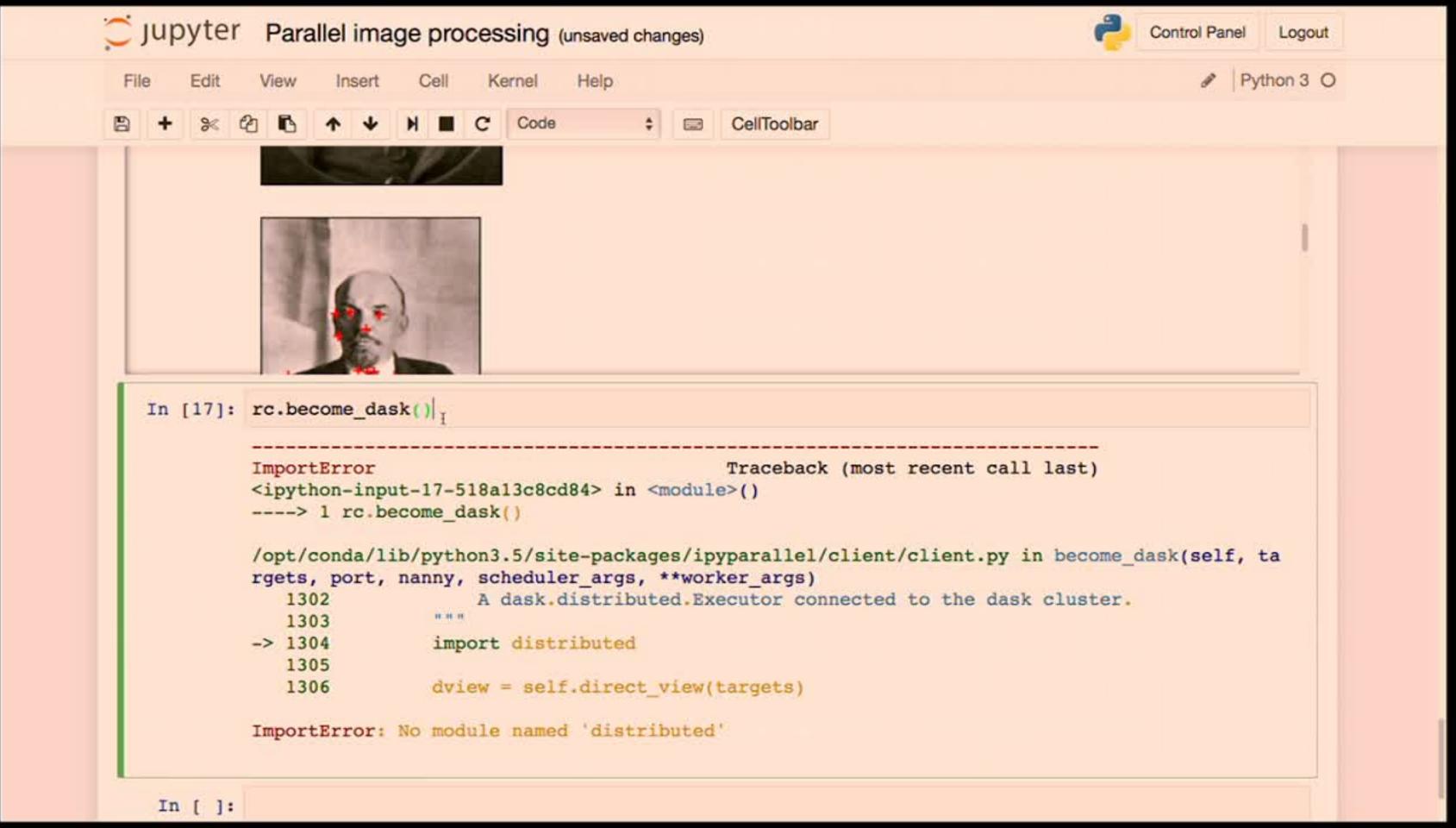


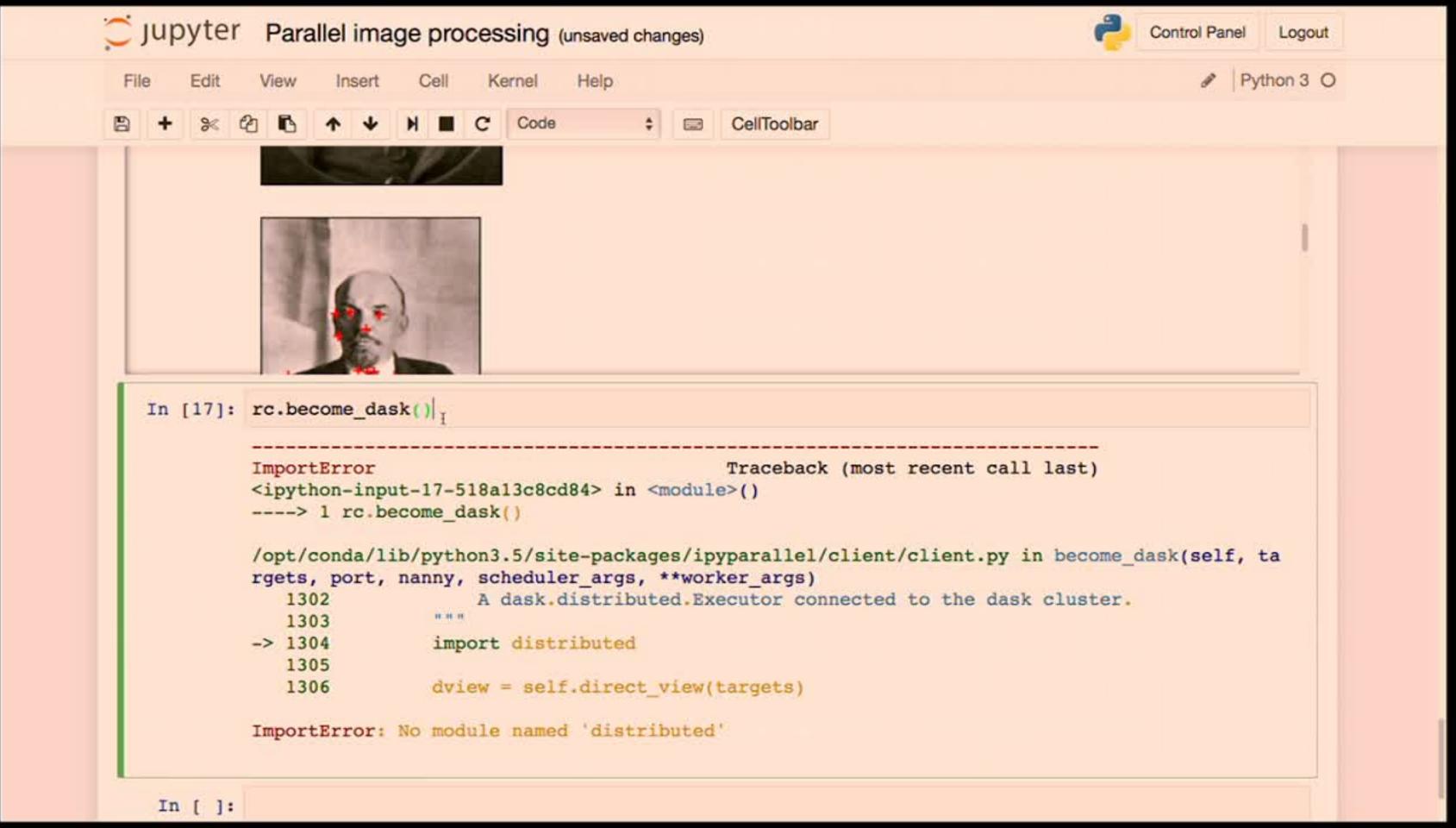


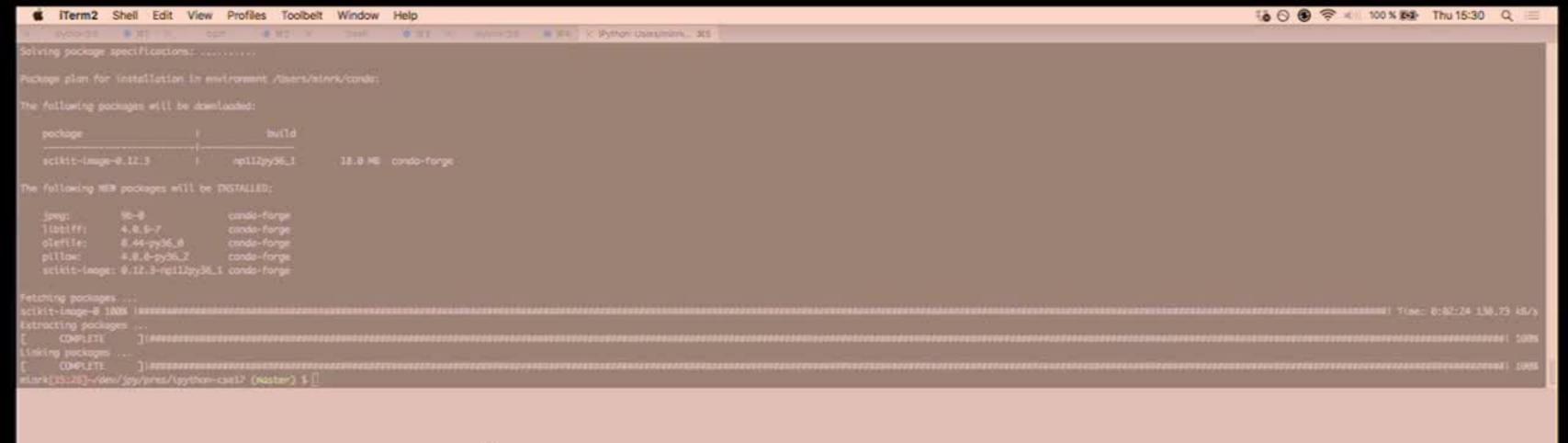
In [ ]:

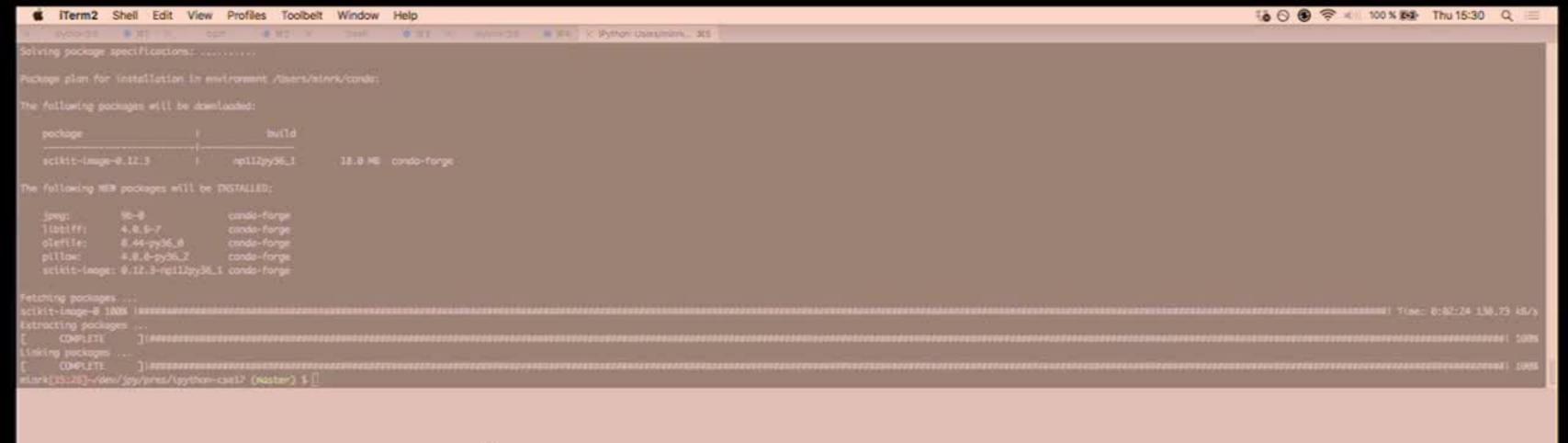


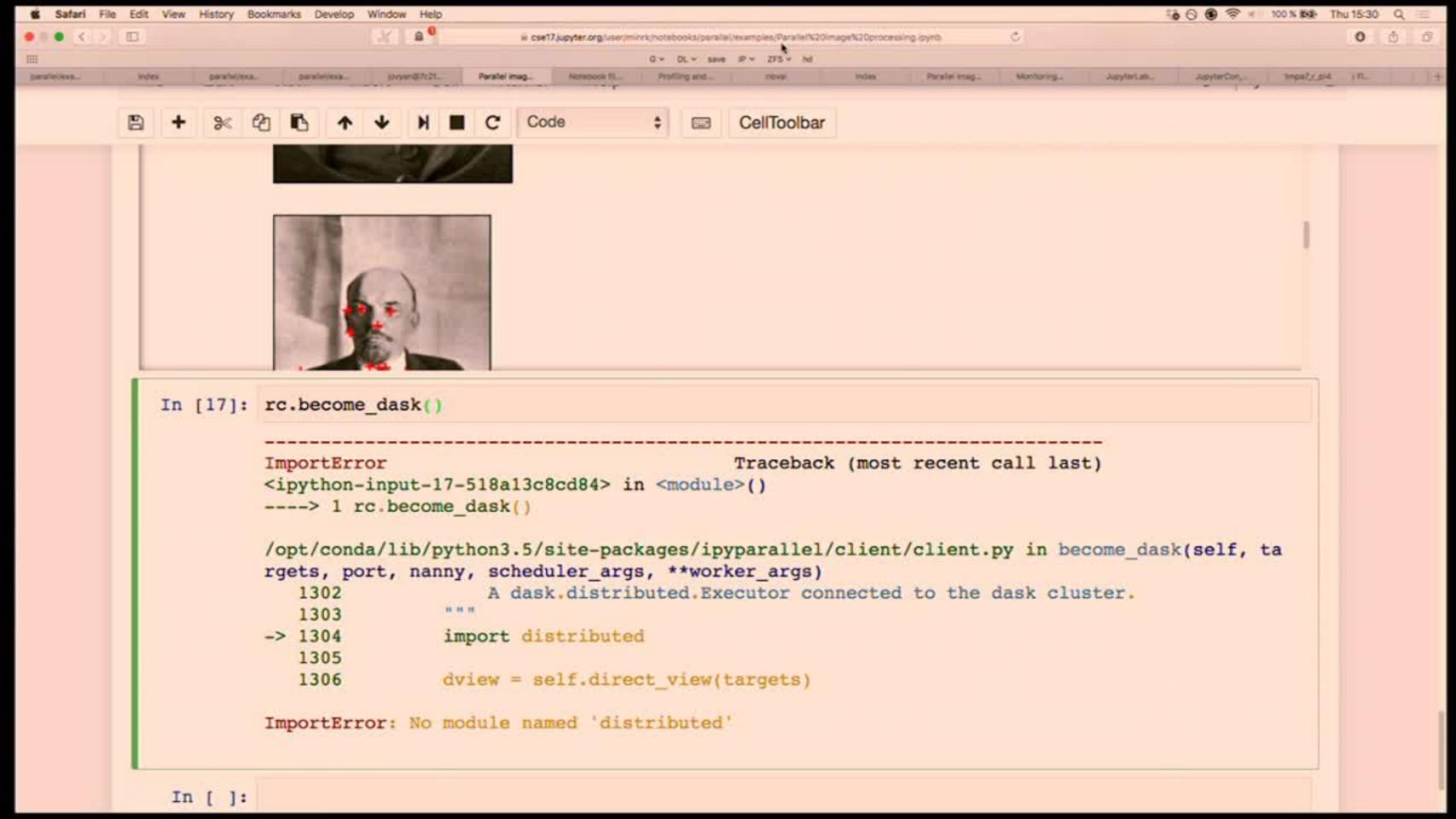


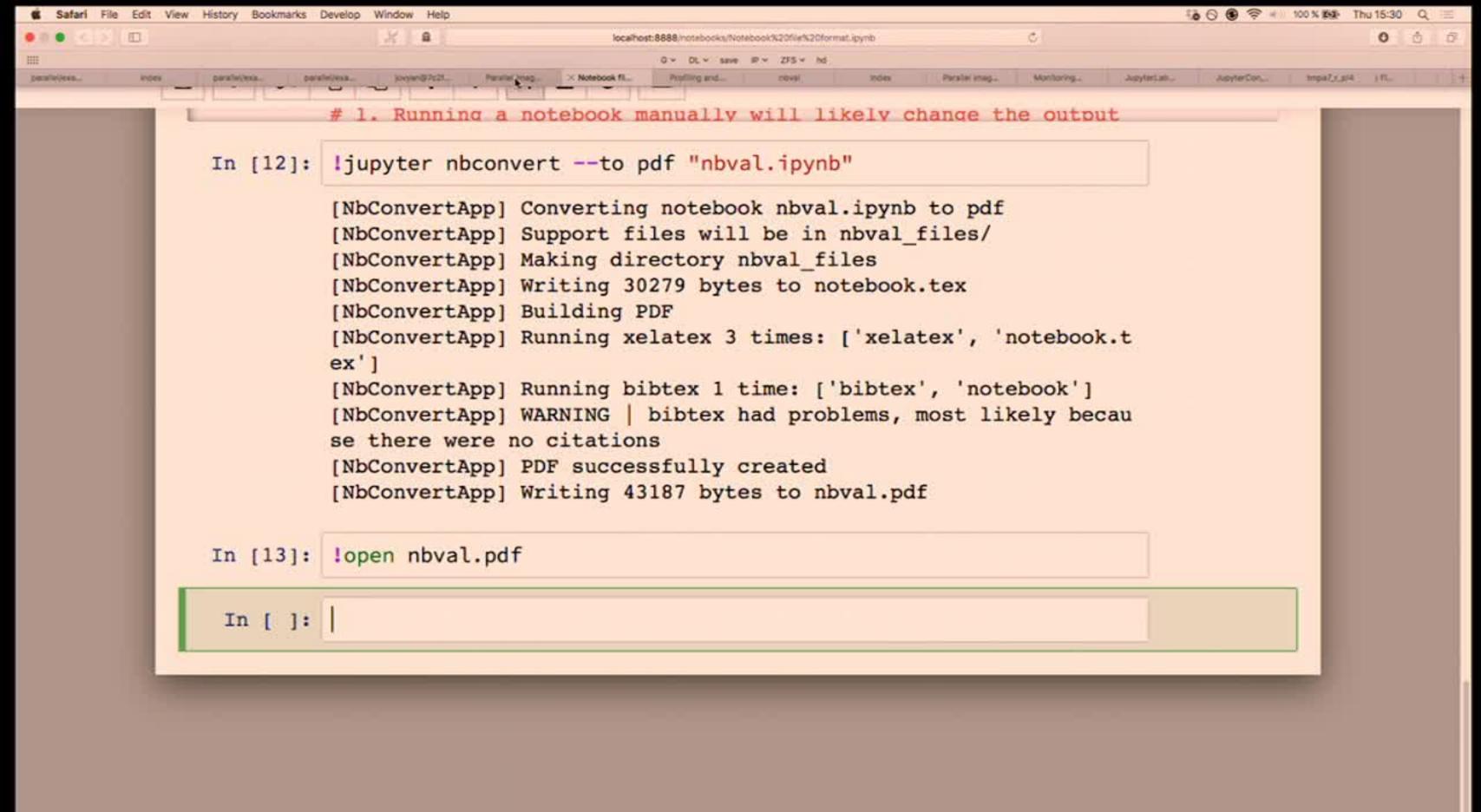




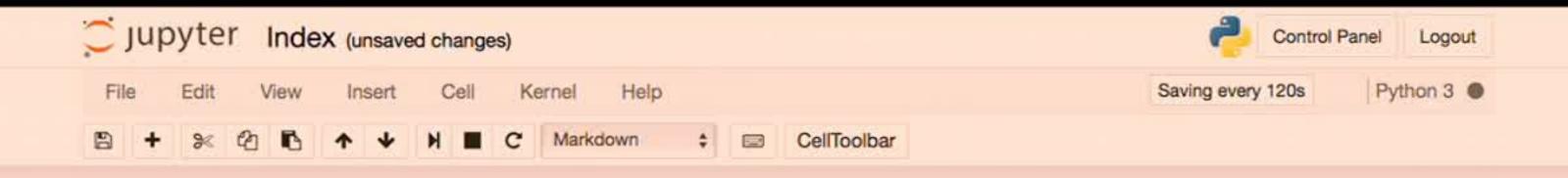












### Interactive (parallel) Python

### Installation and dependencies

You will need ipyparallel >= 5.x, and pyzmq ≥ 13. To use the demo notebooks, you will also need tornado ≥ 4. I will also make use of numpy and matplotlib. If you have Canopy or Anaconda, you already have all of these.

Quick one-line install for IPython and its dependencies:

pip install ipyparallel

Or get everything for the tutorial with conda:

conda install anaconda mpi4py

For those who prefer pip or otherwise manual package installation, the following packages will be used:

ipython ipyparallel numpy matplotlib networkx scikit-image requests beautifulsoup mpi4py

Optional dependencies: I will use <u>NetworkX</u> for one demo, and scikit-image for another, but they are not critical. Both packages are in in Anaconda.

For the image-related demos, all you need are some images on your computer. The notebooks will try to fetch images from Wikimedia Commons, but since the networks can be untrustworty, we have bundled some images here.

Python 3 O



### **Using Parallel Magics**

IPython has a few magics for working with your engines.

This assumes you have started an IPython cluster, either with the notebook interface, or the ipcluster/controller/engine commands.

```
In [1]: import ipyparallel as parallel
    rc = parallel.Client()
    rc.block = True
    dv = rc[:]
    rc.ids

Out[1]: [0, 1, 2, 3]

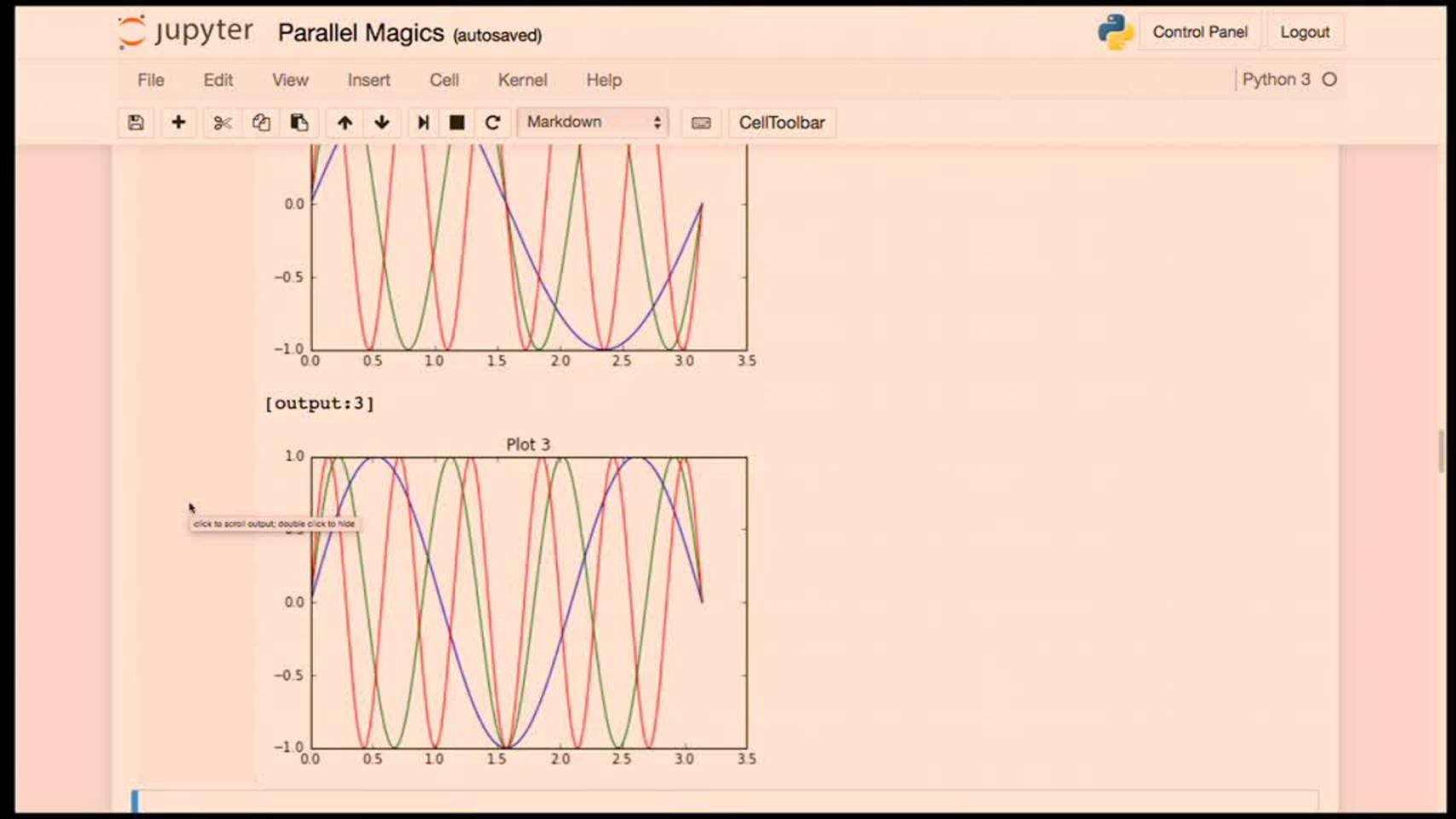
In [2]: dv.apply(lambda x: x * 2, 5)
Out[2]: [10, 10, 10, 10]
```

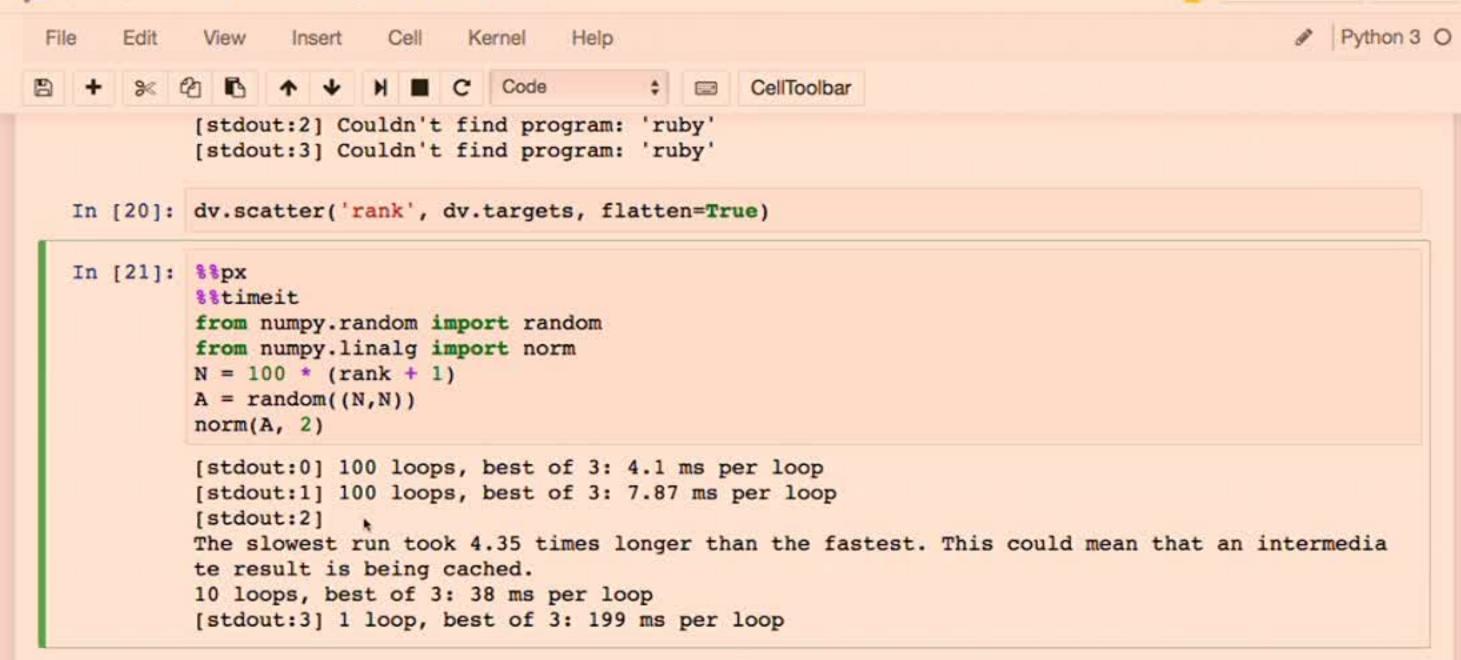
Creating a Client registers the parallel magics %px, %px, %pxresult, pxconfig, and %autopx.

These magics are initially associated with a DirectView always associated with all currently registered engines.

Now we can execute code remotely with %px:

In [241: %px a=5

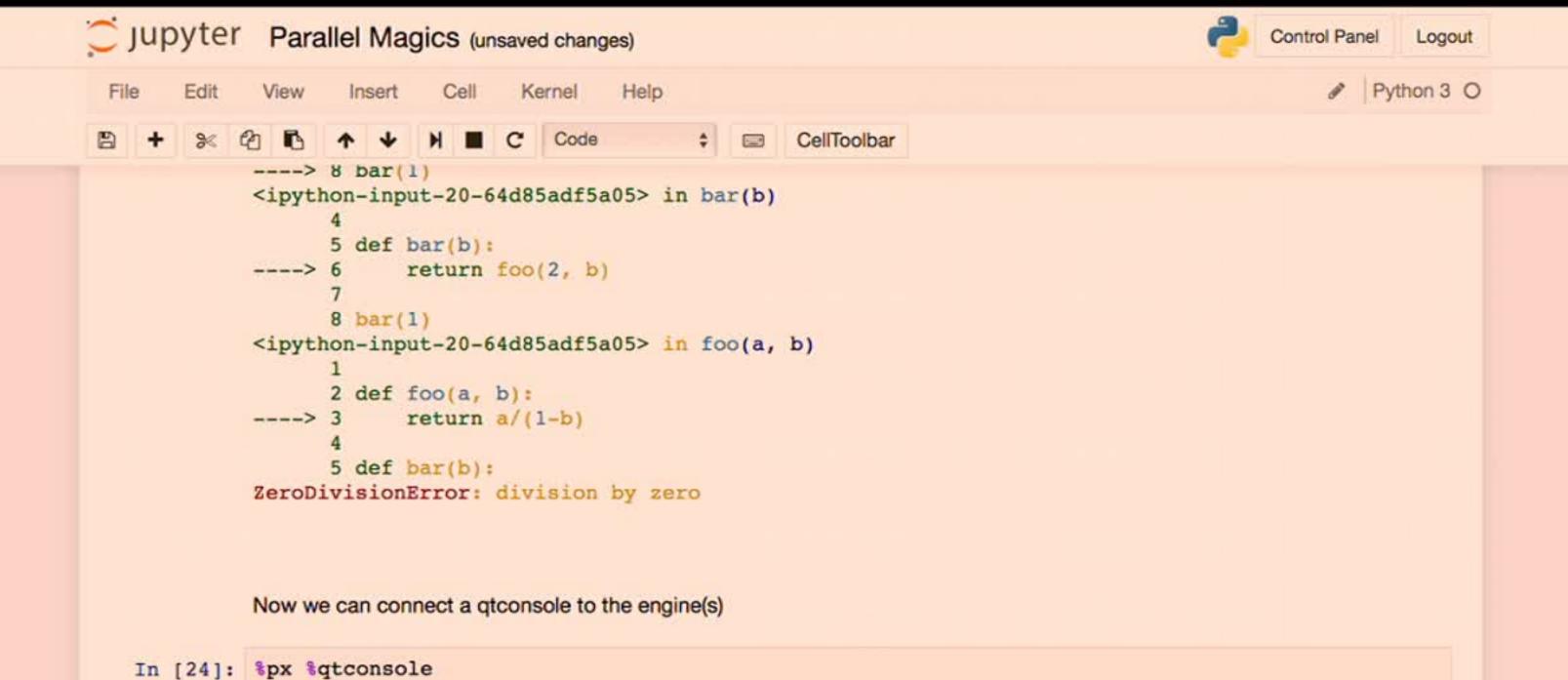




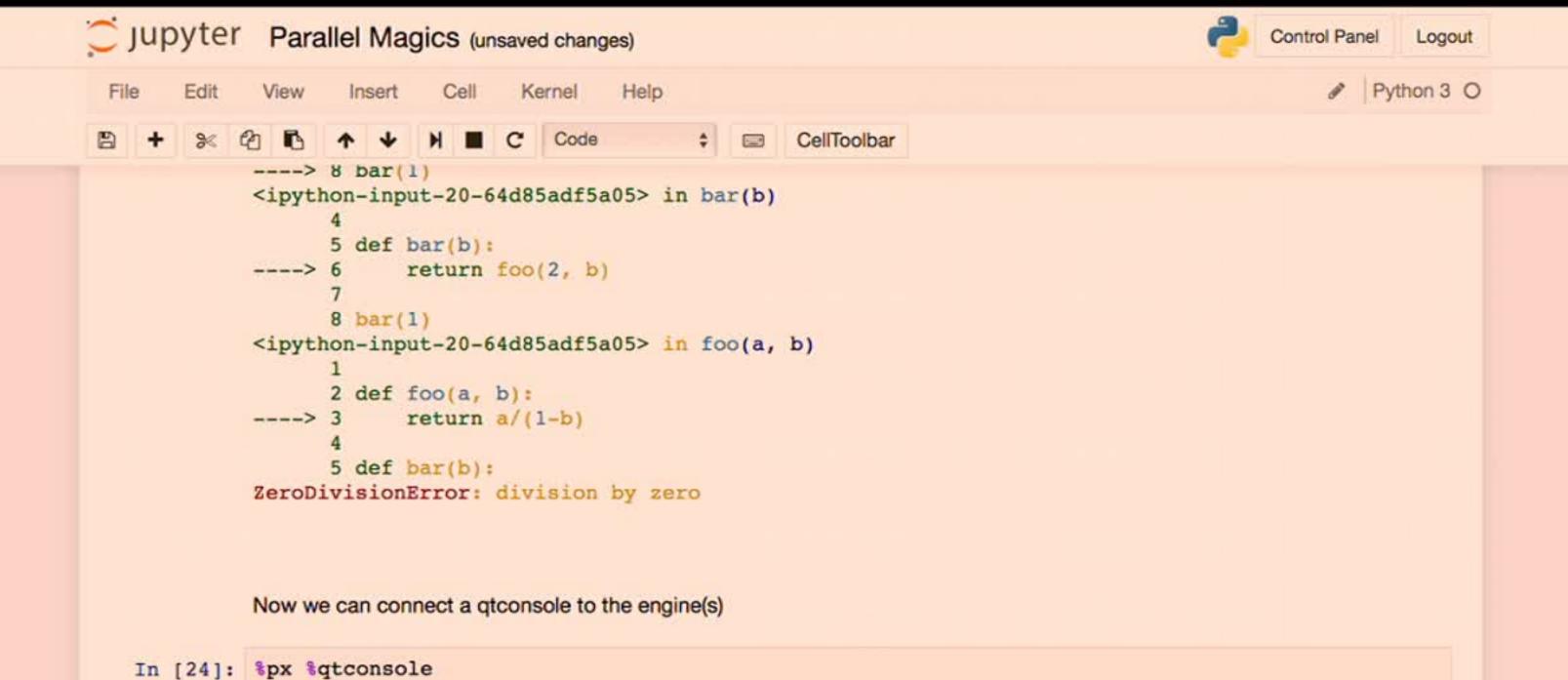
### **Debugging Engines**

Since the IPython engine is precisely the same object used for the notebook and qtconsole, we can connect other fronteds directly to the engine.

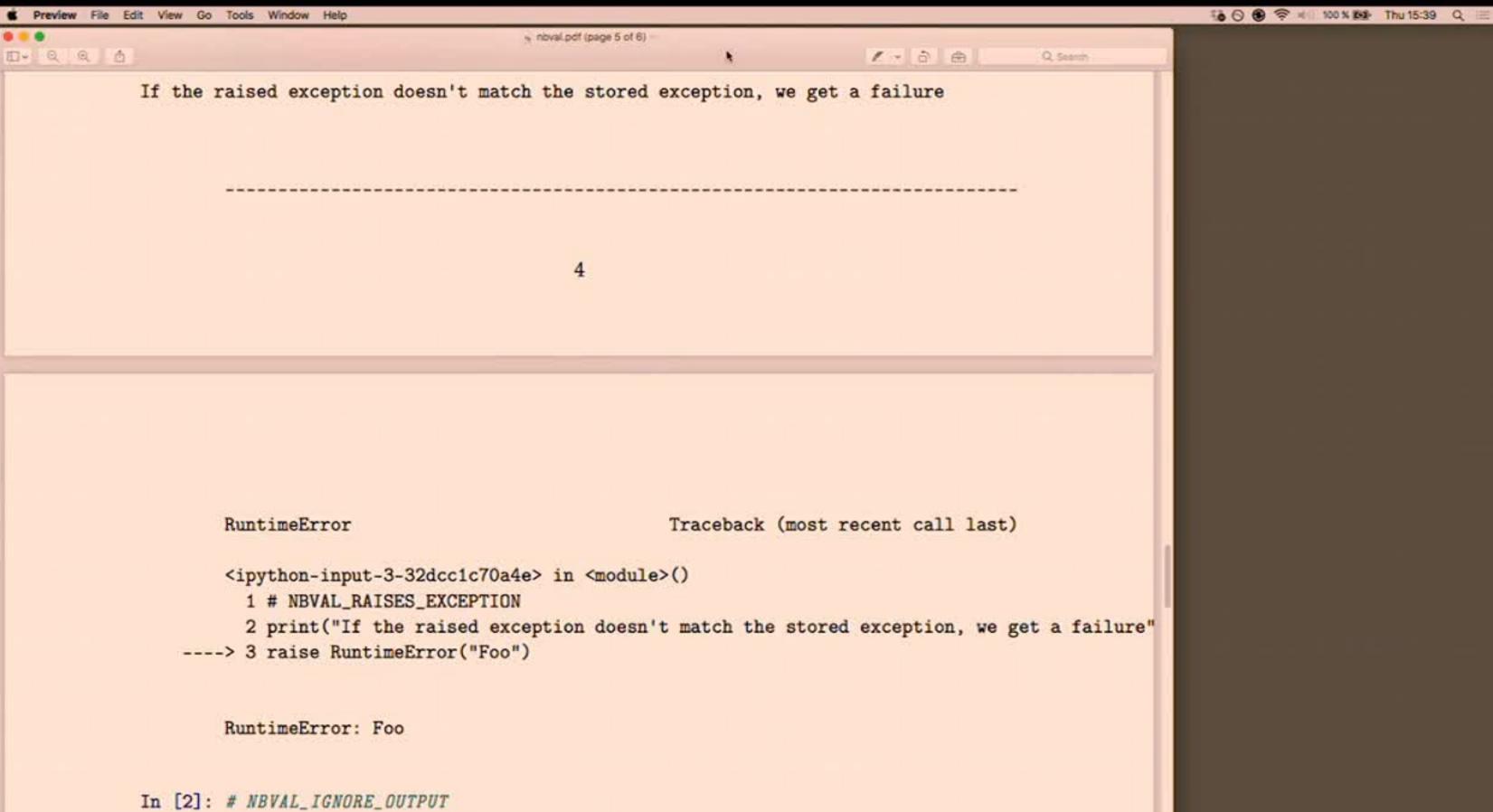
The first step is to bind the engine's sockets, so its connection pattern looks like a regular kernel



In [ ]:



In [ ]:



```
*** NameError: name 'btr' is not defined

ipdb> bt
> <ipython-
input-16-05c9758a9c21>(1)<module>(
)
----> 1 1/0

ipdb>
```

If the raised exception doesn't match the stored exception, we get a failure

-----

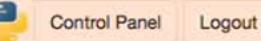
```
*** NameError: name 'btr' is not defined

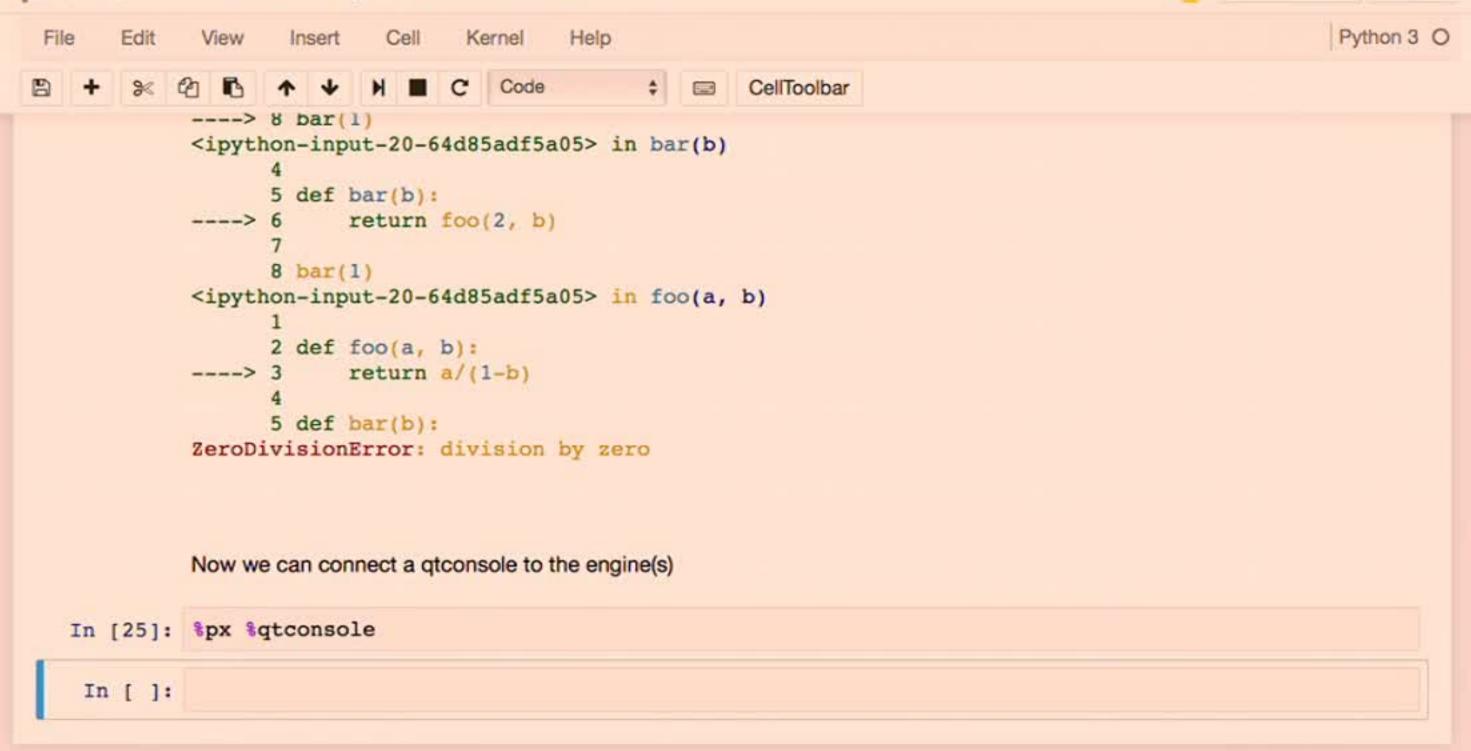
ipdb> bt
> <ipython-
input-16-05c9758a9c21>(1)<module>(
)
----> 1 1/0

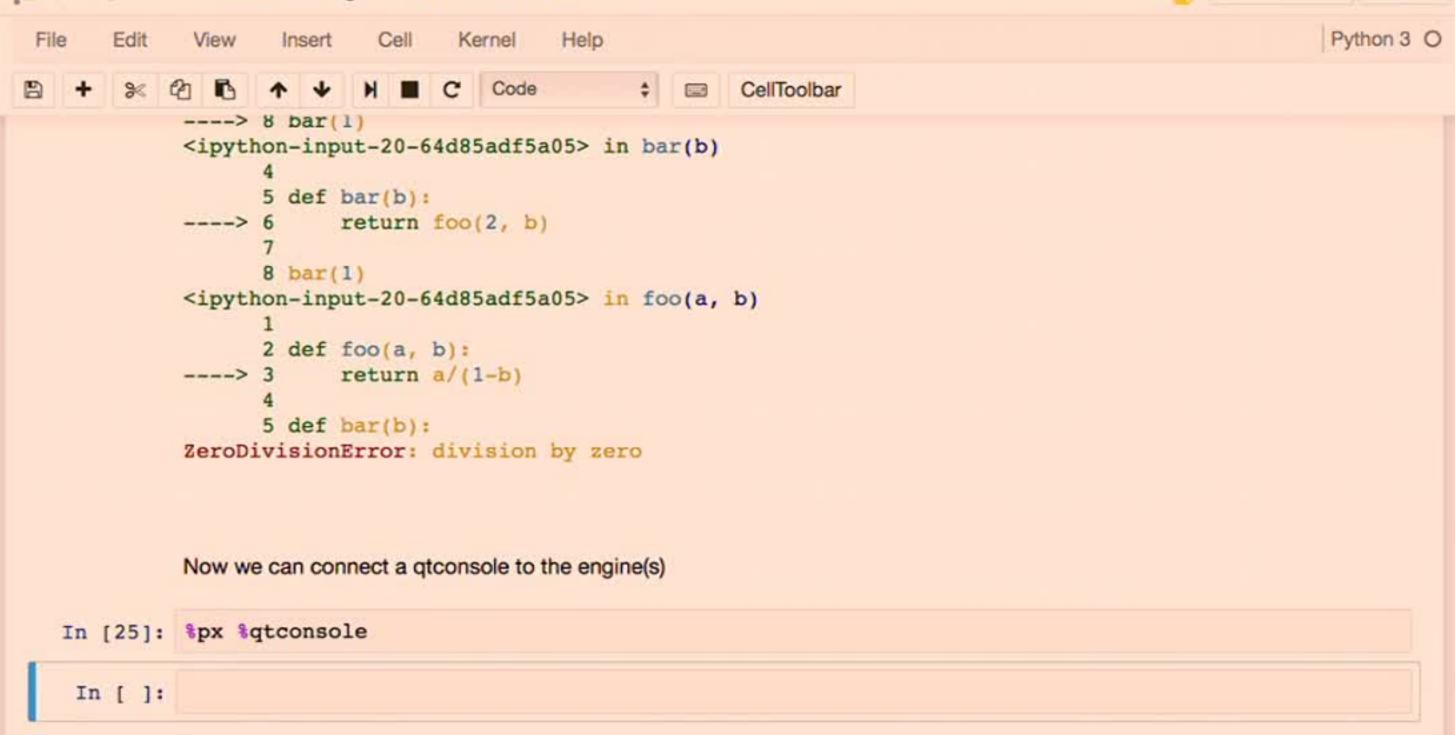
ipdb>
```

If the raised exception doesn't match the stored exception, we get a failure

-----







```
*** NameError: name 'btr' is not defined

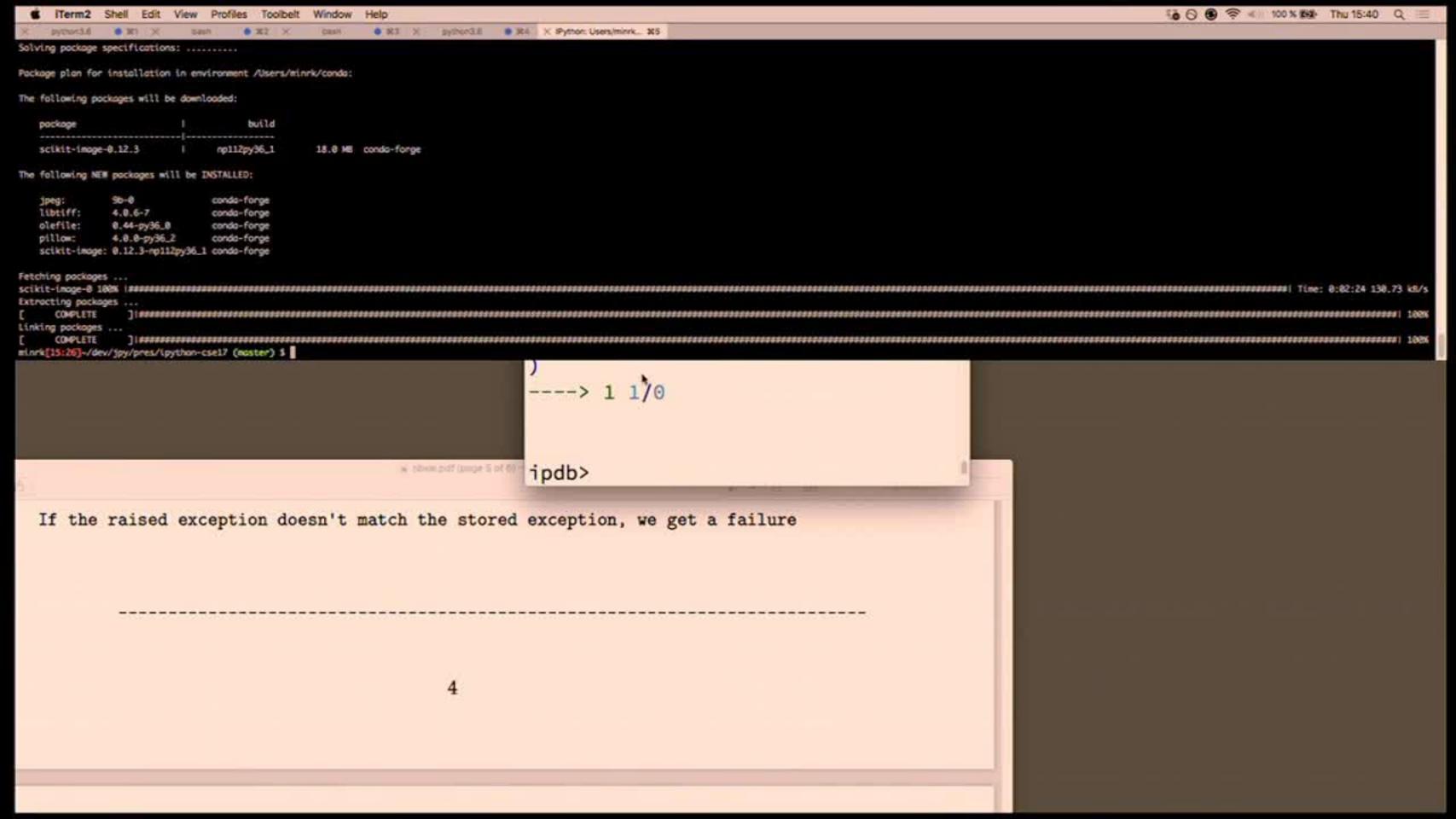
ipdb> bt
> <ipython-
input-16-05c9758a9c21>(1)<module>(
)
----> 1 1/0

***NameError: name 'btr' is not defined

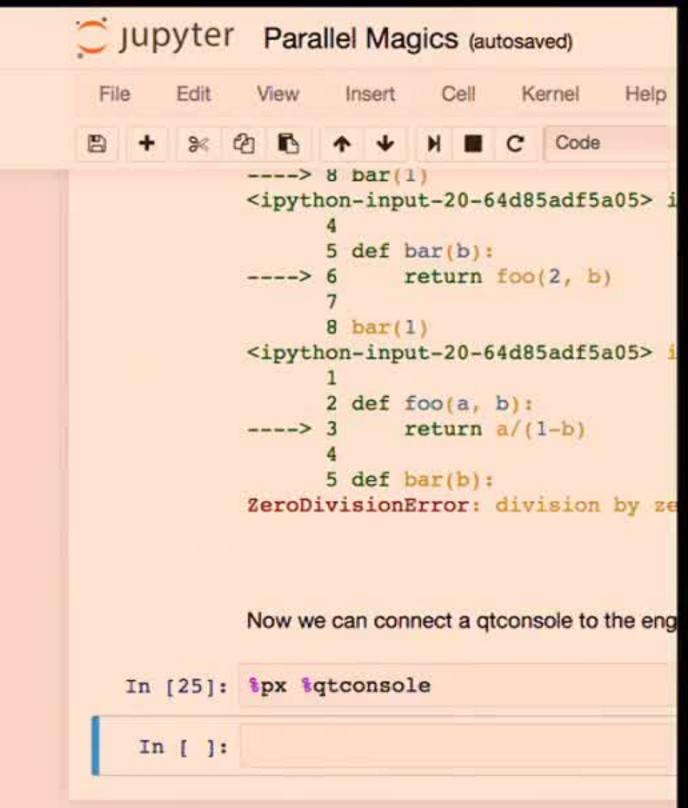
ipdb> bt
> <ipython-
input-16-05c9758a9c21>(1)<module>(
)
```

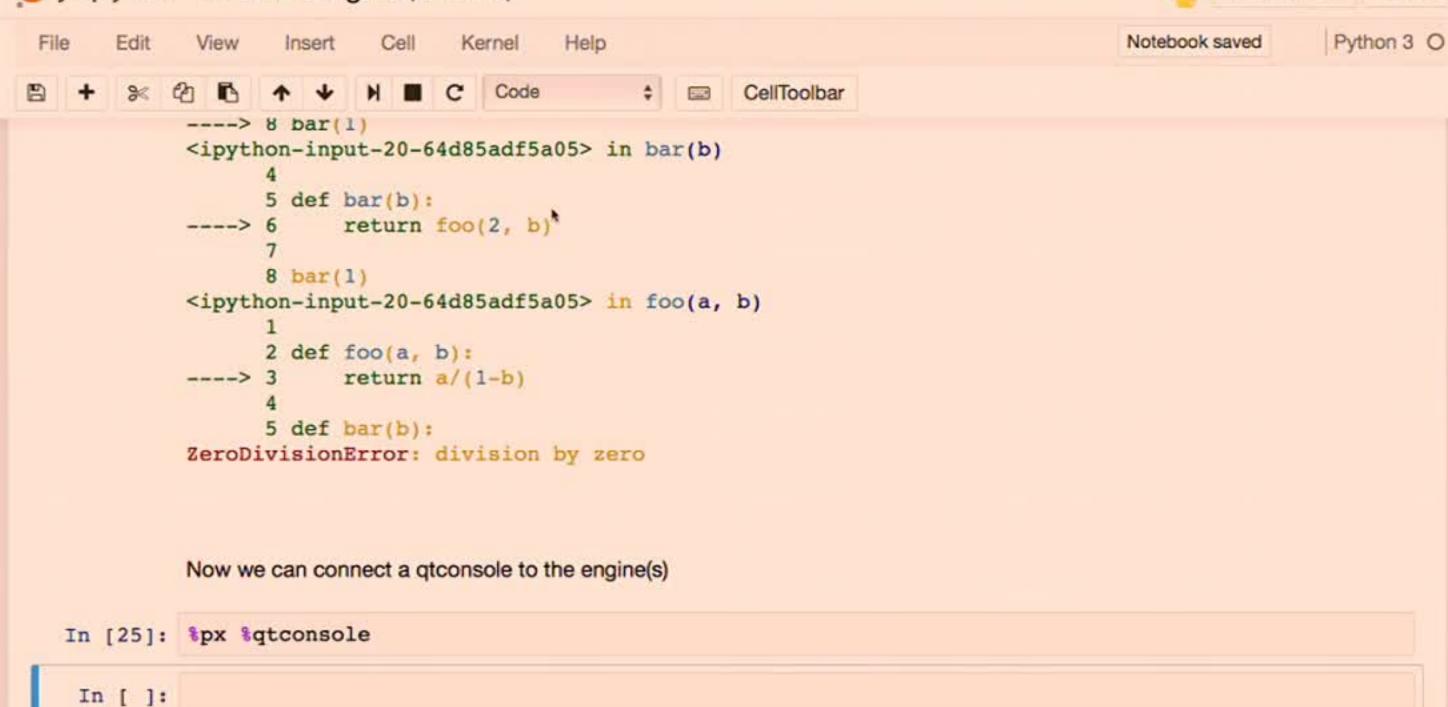
If the raised exception doesn't match the stored exception, we get a failure

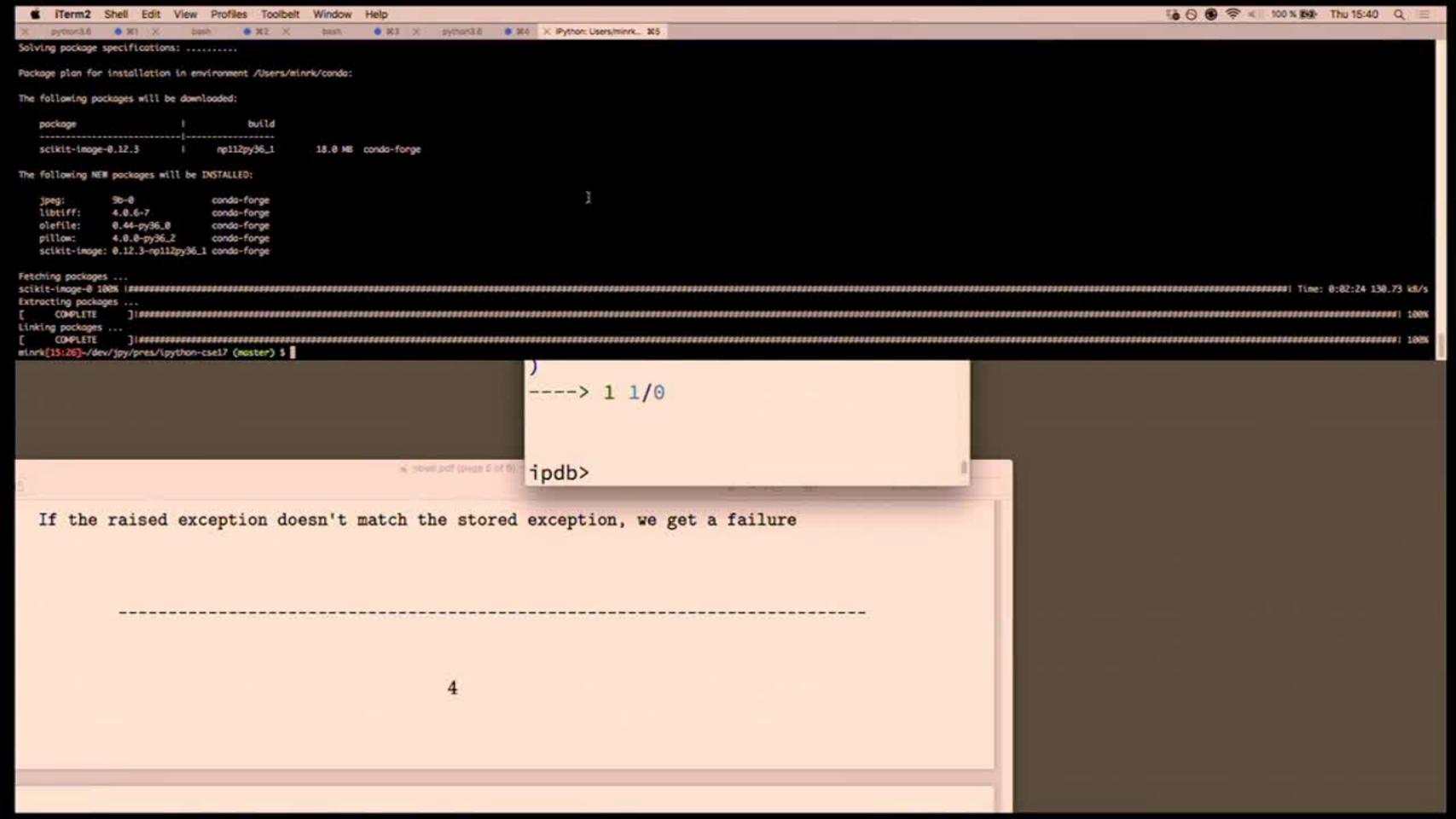
.....

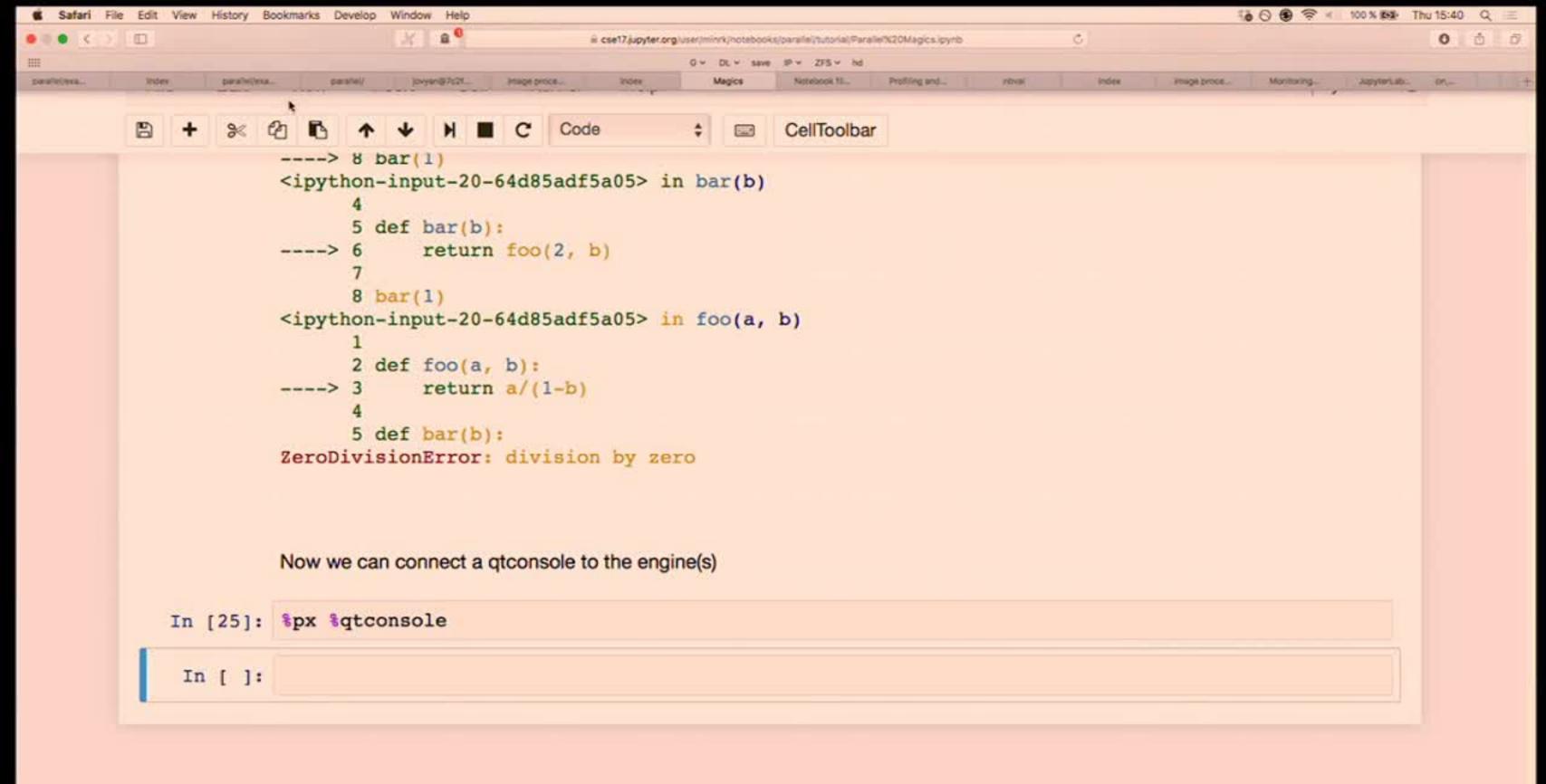


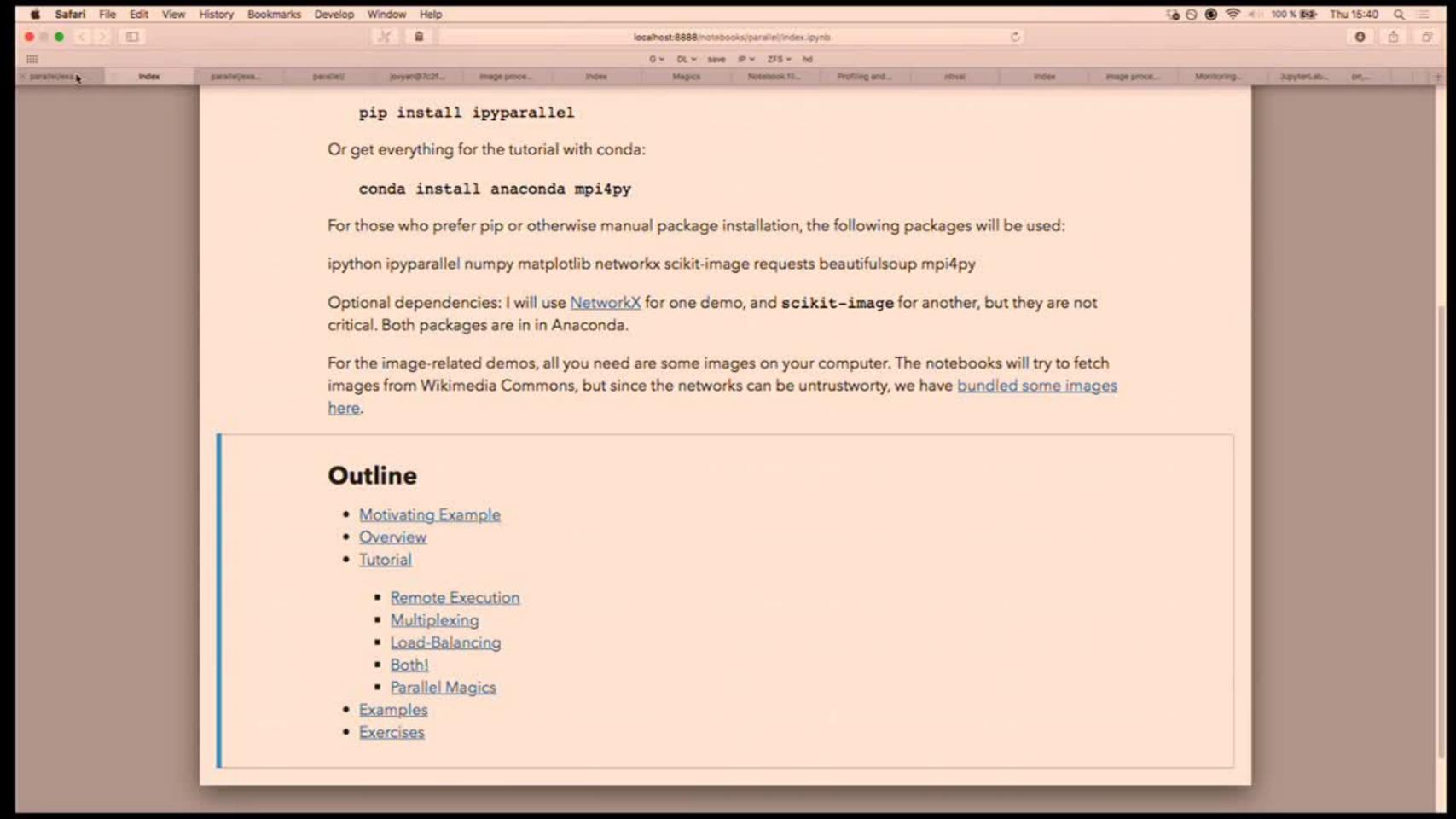
```
100 % € Thu 15:40 Q =
 Jupyter OtConsole
r: name 'btr' is not
9758a9c21>(1)<module>(
et a failure
```

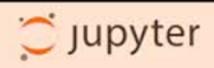












Files Running IPython Clusters	
Select items to perform actions on them.	Upload New → 2
parallel	Name ↑ Last Modified ↑
□	seconds ago
□ □ examples	18 minutes ago
exercises	2 hours ago
☐ ☐ figs	2 hours ago
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□ tutorial	an hour ago
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## Interactive (parallel) Python

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#### Outline

- Motivating Example
- Overview
- Tutorial
  - Remote Execution
  - Multiplexing
  - Load-Balancing
  - · Both!
  - Parallel Magics
- Examples
- Exercises



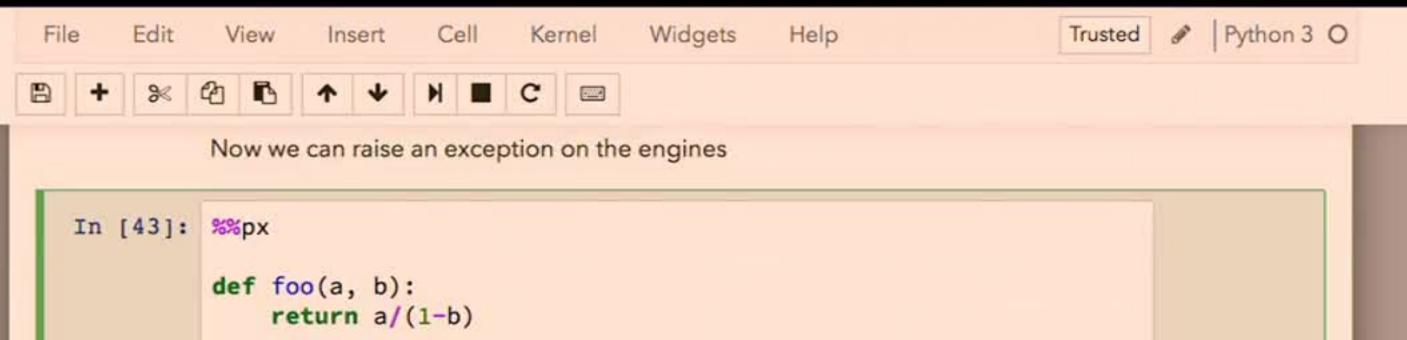
# **Using Parallel Magics** ¶

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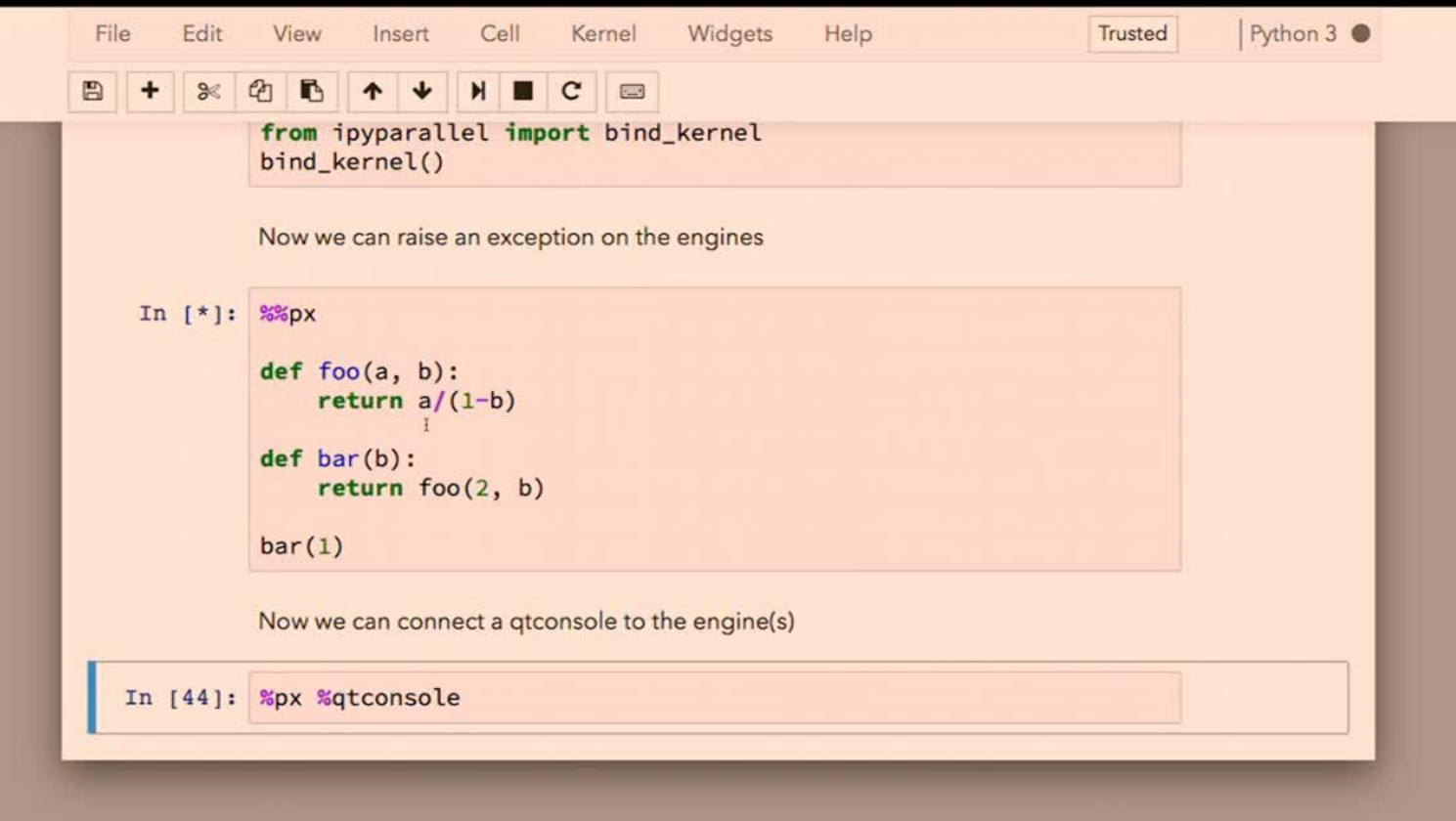
This assumes you have started an IPython cluster, either with the notebook interface, or the ipcluster/controller/engine commands.

```
In [23]: import ipyparallel as parallel
    rc = parallel.Client()
    rc.block = True
    dv = rc[:]
    rc.ids
```

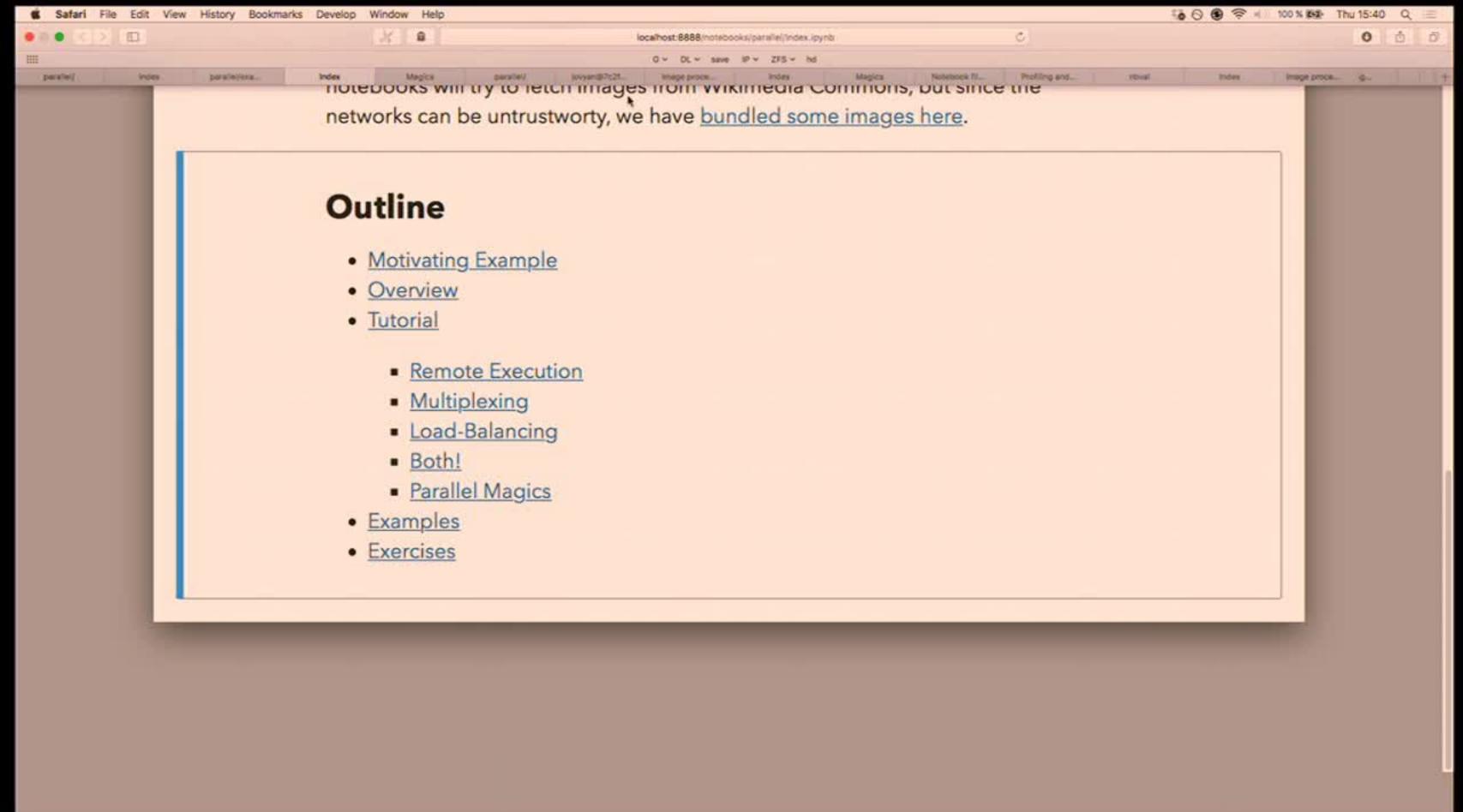
Out[23]: [0, 1, 2, 3]

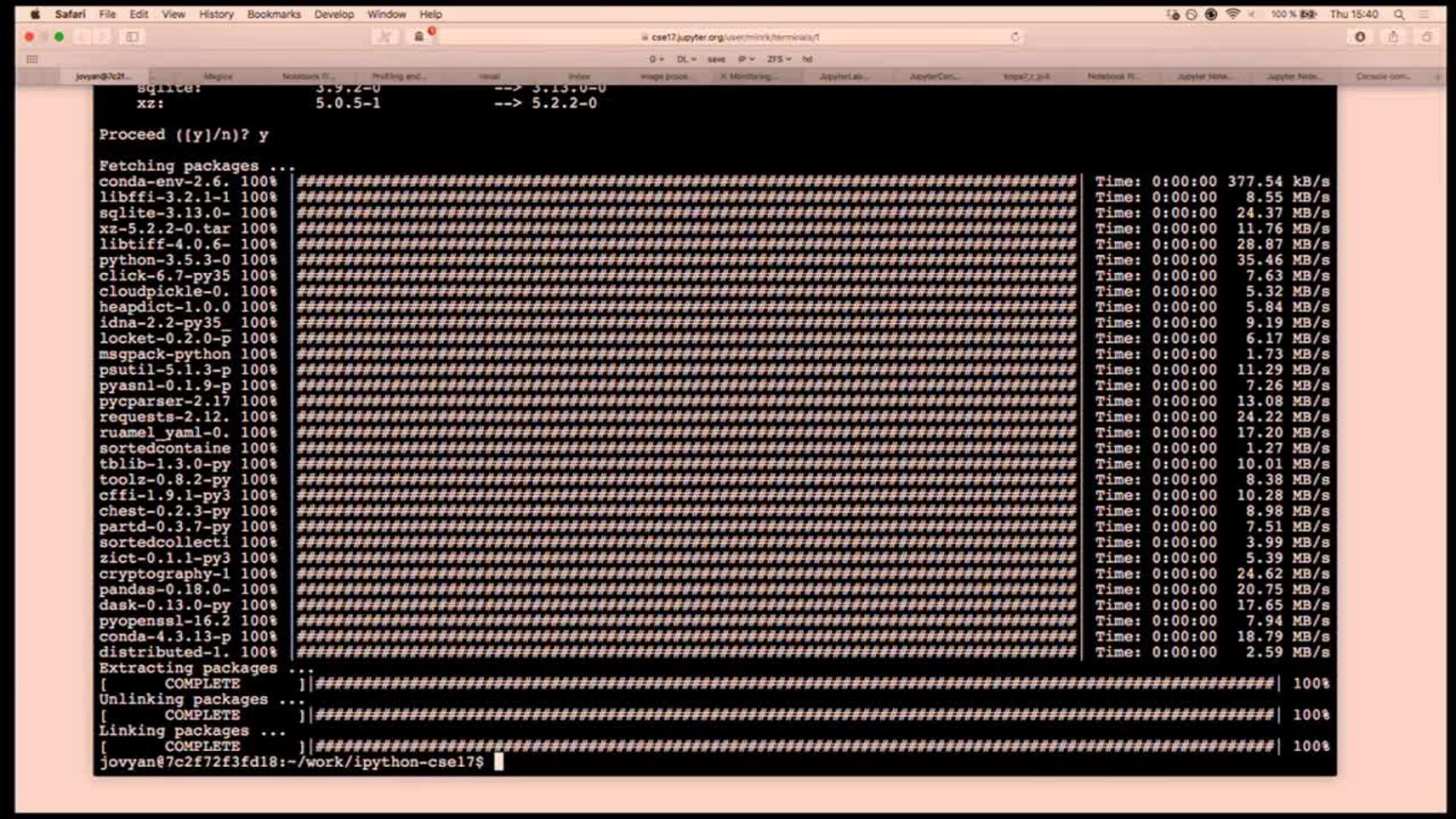


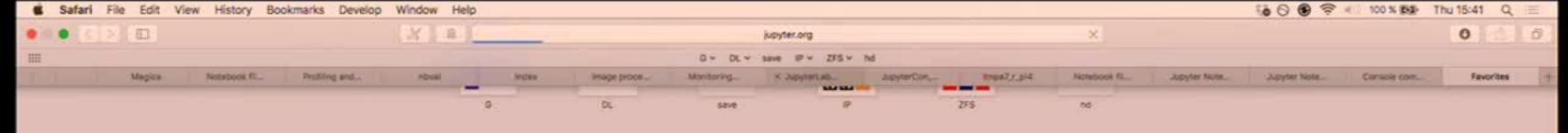
```
def bar(b):
   return foo(2, b)
bar(1)
[0:execute]:
-----ZeroDivisionError
                                                     Traceback
(most recent call last)<ipython-input-31-64d85adf5a05> in <modu
le>()
           return foo(2, b)
---> 8 bar(1)
<ipython-input-31-64d85adf5a05> in bar(b)
      5 def bar(b):
---> 6 return foo(2, b)
     8 bar(1)
<ipython-input-31-64d85adf5a05> in foo(a, b)
```











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