FORMULA: FactORized MUlti-task LeArning for task discovery in personalized medical models

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Outline

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- Personalized medical predictive modeling
- Related works
- The proposed FORMULA Framework
- Experiments and Results
- Conclusion

Personalized Medical Predictive Modeling

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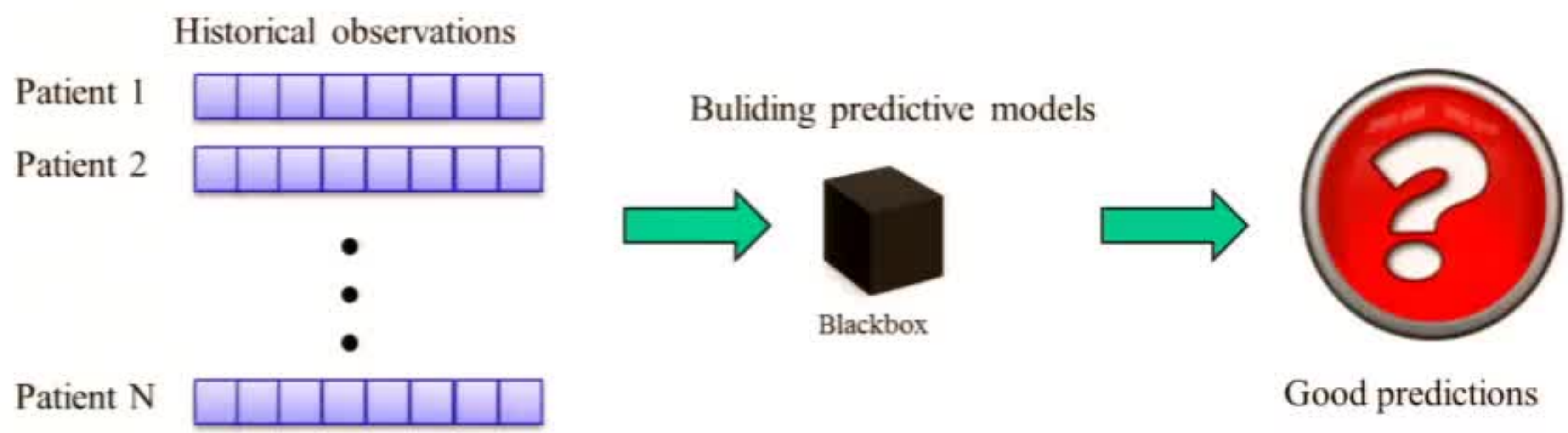
- The amount of patient record data is growing with the development and availability of electronic medical records (EMR)
- The patients' medical records are leveraged by practitioners in applications for clinical decision support and care management systems by performing various predictive modeling tasks for risk predictions and disease analysis.



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Personalized Medical Predictive Modeling

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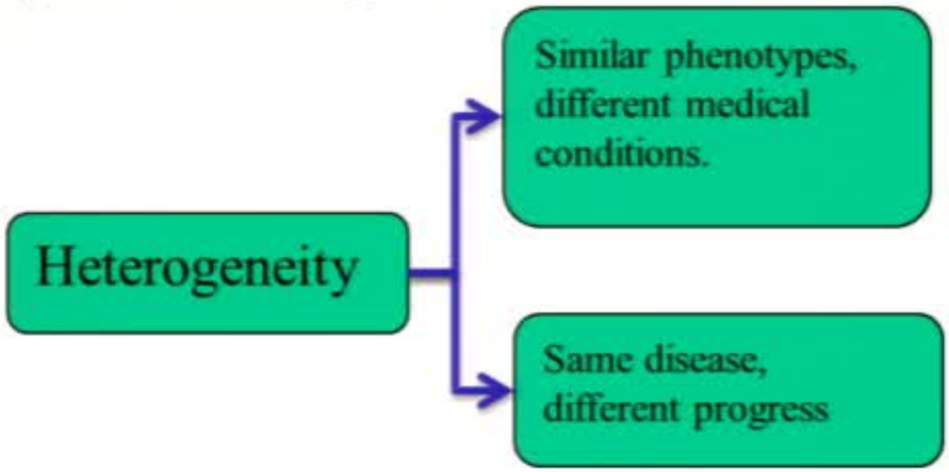
- Challenges: Heterogeneous nature of the patients



- How can we address this heterogeneity nature?

Personalized models

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Personalized Medical Predictive Modeling

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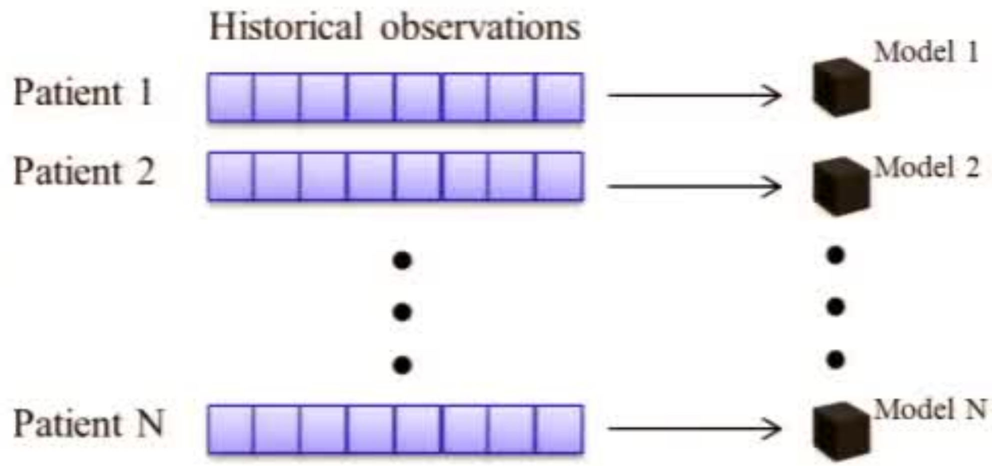
- A simple personalized modeling: learning independently



- Pros:
  - The idea is simple and straightforward.
- Cons:
  - It is not efficient in terms of time and space complexity when task number is large
  - The models will be likely to severely overfit the data due to the limited amount of training data and result in poor generalization performance

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Personalized Medical Predictive Modeling

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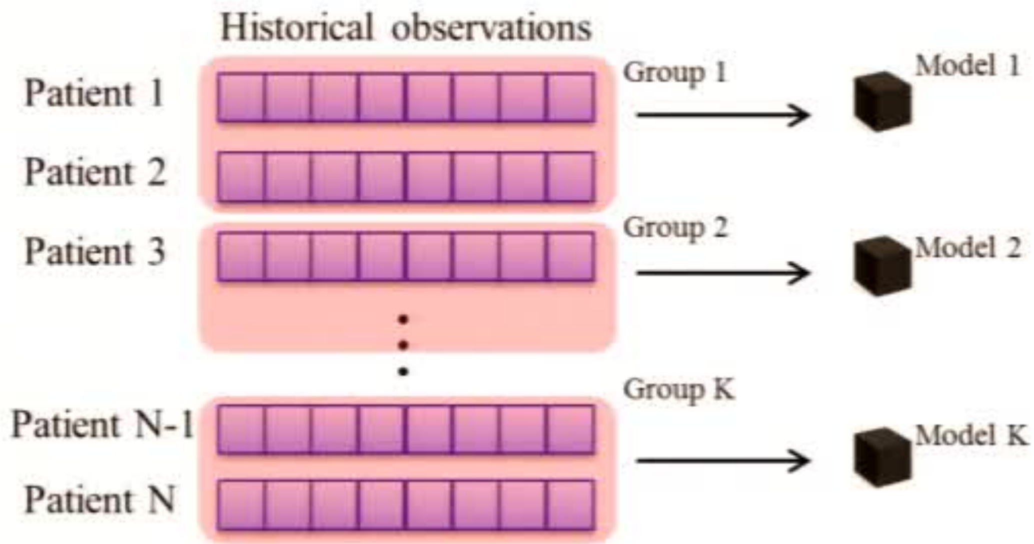
- A two-stage modeling method: grouping + modeling on each group



Examples:
Locally weighted learning
Localized support vector machine
Clustering + MTL

- Pros:
  - The number of models built are reduced
  - The number of training data is increased in each model building process
- Cons:
  - Grouping and model building are separate procedures, which could reach into suboptimal results
  - Building models for each group independently does not utilize potential valuable information from patients in other groups.
  - The models are not fully personalized as the patients within a group will have the same model

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Personalized Medical Predictive Modeling

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- Motivation:
  - **Personalized modeling**: build one model for each of the patient
  - **Patients grouping**: find hidden heterogeneity base models between patients
- Contribution:
  - we proposed a novel approach called FactORized MUlti-task LeArning model (FORMULA)
  - FORMULA extracts the base models of the patients and uses a linear combination of these models as the personalized model of a patient
  - FORMULA employs a sparse matrix factorization formulation to perform base model selection for each patient and feature selection for each base model.
  - We evaluated FORMULA on the Alzheimer's Disease Neuroimaging Initiative (ADNI) database. The experimental results show the superiority of FORMULA over other baseline methods

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Related works

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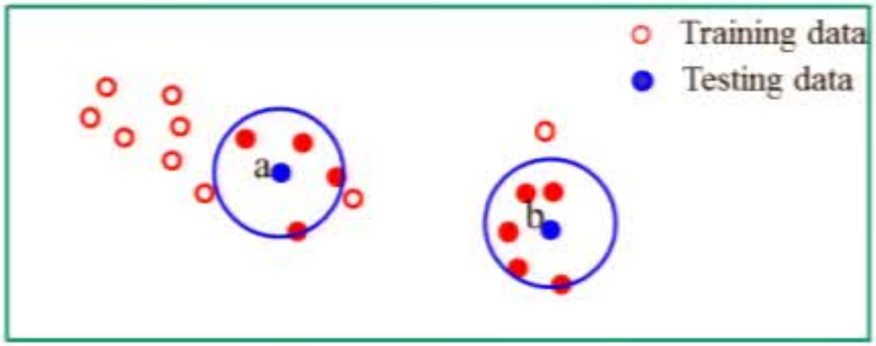
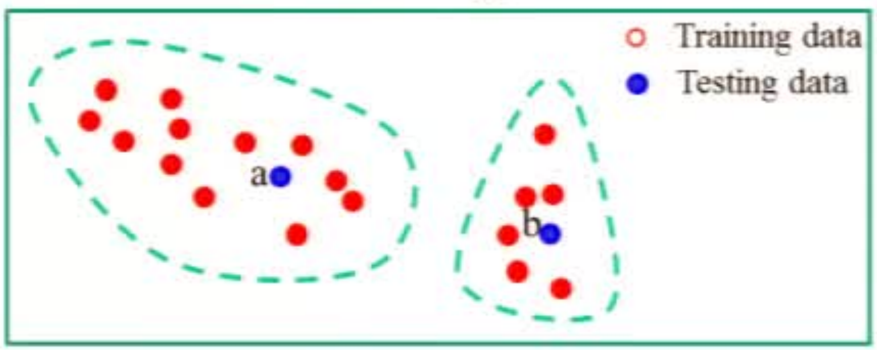
Locally weighted learning: lazy learning, building a model for each of the test data point



Drawbacks:

- Build a model for each test data points

Localized SVM: building a model for each group of the data point



Drawbacks:

- Need all testing points in advance
- Not a fully personalized modeling procedure

Related works

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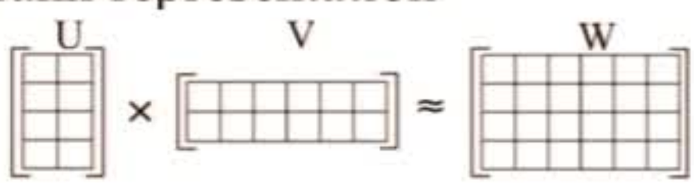
Multi-task Learning: learning models for multiple tasks simultaneously by considering the information shared between tasks

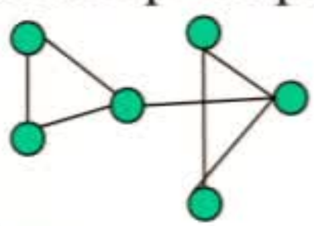
- Information sharing schemes:
  - Low-rank representation



Constraint

$$W = UV$$

  - Relationship Graph



Regularization

$$\sum_{i,j} A_{i,j} \|\mathbf{w}_i - \mathbf{w}_j\|_2^2$$

- Drawbacks:
  - Tasks are defined in advance.
  - It can be only used in two-stage modeling method as Clustering + MTL.

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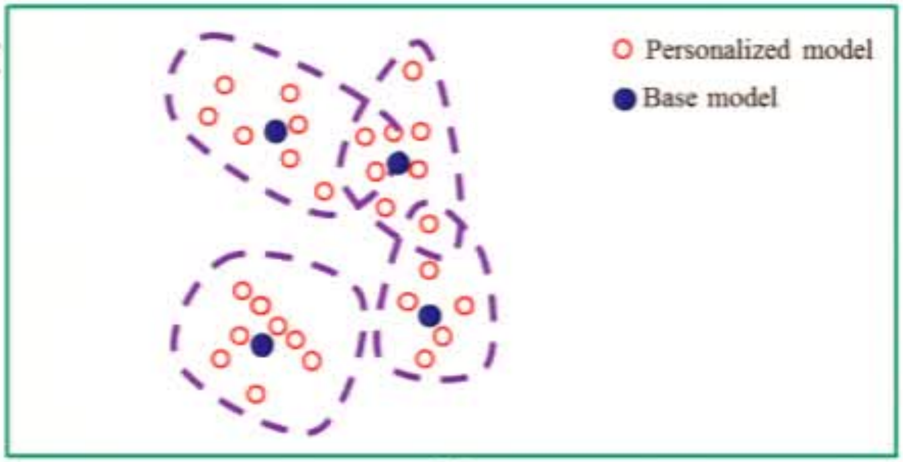
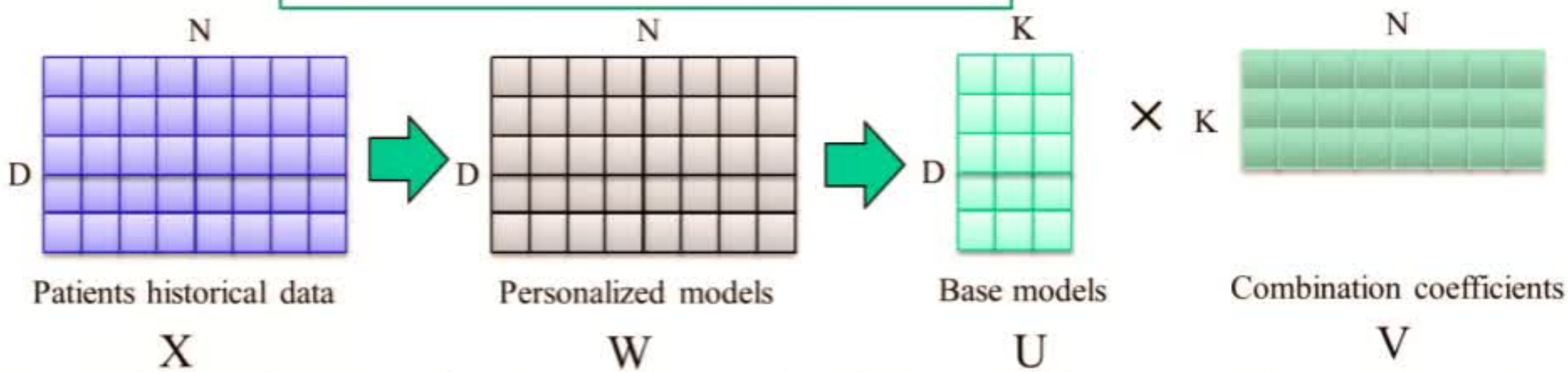
Basic idea:



Note: Grouping on models instead of data points



In order to learn robust and meaningful models, we enforce sparsity on U and V

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Local Smoothness and Recovery:

- We assume the models for patients with similar phenotypes should be close to each other
- Such a model smoothness criterion is helpful to infer the personalized model for a test patient by assuming it is similar to the weighted average of the personalized models for its neighbors

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Objective function:

Squared loss function

Sparsity on combination coefficients

$$\min_{W,U,V} \frac{1}{2} \boxed{\sum_i^N (y_i - \mathbf{w}_i^T \mathbf{x}_i)^2} + \lambda_1 \boxed{\|V\|_1}$$

$$+ \lambda_2 \boxed{\|U\|_1} + \frac{\lambda_3}{2} \boxed{\|W - WL\|_F^2}$$

$$\text{s.t. } V \succeq 0, \boxed{W = UV}$$

Sparsity on base models

Local Smoothness and Recovery

Task grouping and modeling

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Experiments and Results

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Experiment setting:

- Data source: Alzheimer's disease Neuroimaging Initiative (ADNI) database
- Dataset: 10 datasets are created based on the elapsed time since the initial hospital visit

Table 1: Dataset size of ADAS-Cog and MMSE

	M06	M12	M24	M36	M48
ADAS-Cog	648	638	564	377	85
MMSE	648	642	569	389	87

- Baselines
  - SM: Single model with Ridge regression
  - CSTR: Clustering + single task model with Ridge regression
  - CSTL: Clustering + single task model with Lasso regression
  - CSL: Clustering + sparse low-rank MTL
  - CMR: Clustering + mean regularized MTL

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Experiments and Results

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Results:

Table 2: Comparison the MSE between FORMULA and baseline methods

MSE	ADAS-Cog					MMSE				
	M06	M12	M24	M36	M48	M06	M12	M24	M36	M48
SM	0.497	0.553	**0.758**	**0.893**	2.153	0.237	0.331	0.420	0.536	1.202
CSTR	0.469	0.637	0.879	0.985	1.543	0.246	0.329	0.392	0.493	0.747
CSTL	0.448	0.558	0.817	0.907	**1.416**	0.205	**0.264**	0.287	0.364	0.954
CSL	0.555	0.695	0.869	0.981	1.524	0.247	0.335	0.383	0.470	0.821
CMR	0.545	0.625	0.860	0.978	1.524	0.242	0.319	0.362	0.420	0.786
FORMULA	**0.424**	**0.545**	0.764	0.899	1.520	**0.197**	0.267	**0.262**	**0.347**	**0.673**

Remarks:

- FORMULA outperforms all other baselines in 6 out of 10 datasets
- FORMULA is consistently one of the top two algorithms for all the datasets
- FORMULA vs CSL/CMR: learning the groups and models simultaneously helps to improve the performance.

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MALSAR

MULTI-TASK LEARNING VIA STRUCTURAL REGULARIZATION

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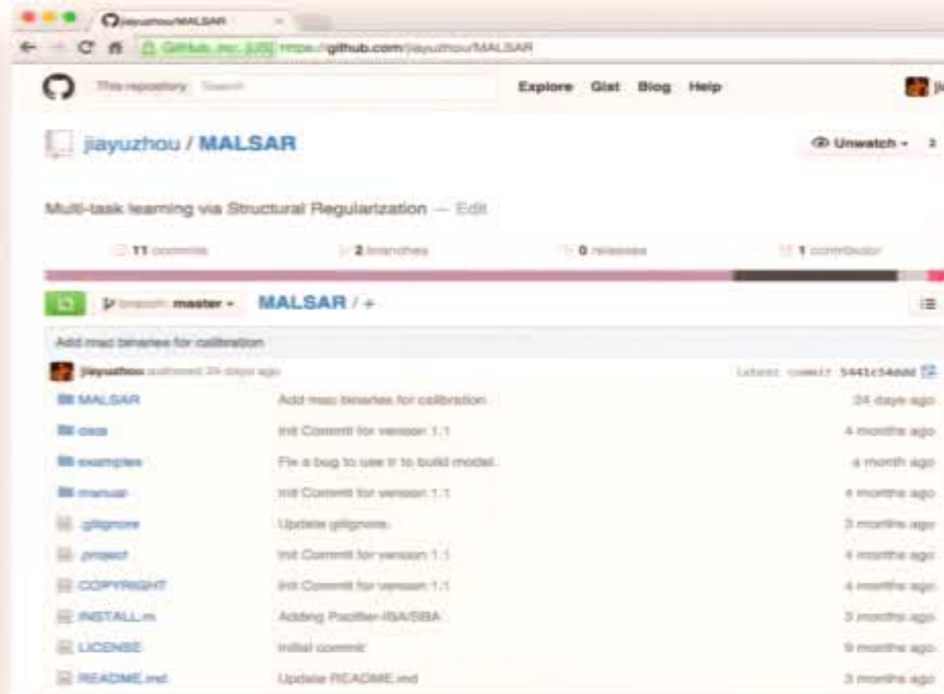

- ⇨ **Efficient solvers of many state-of-the-art multi-task learning formulations;**
- ⇨ **Over 40 research works using MALSAR are published in KDD, NIPS, TPAMI, ICCV, ICDM, ICIP, COLING, MICCAI, ACM-MM, etc;**
- ⇨ **Used as course material to analyze compound profiling in the Strasbourg Summer School in France**

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Conclusion

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- we propose a novel FactORized MUlti-task LeArning model (FORMULA) to learn low-rank personalized models, leveraging the shared information among patients.
- FORMULA employs a sparse matrix factorization formulation to perform base model selection for each patient and feature selection for each base model.
- Our experimental results on the Alzheimer's Disease Neuroimaging Initiative (ADNI) data set suggest that the proposed approach is superior than several baseline method.