



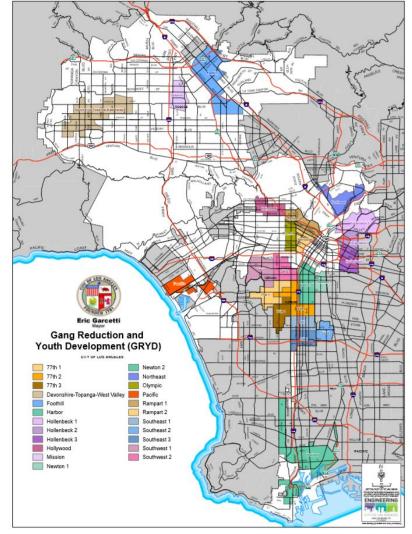
Gang Reduction & Youth Development Project (GRYD)

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- Program conducted by the City of Los Angeles Mayor's Office
- Aims to:
 - Reduce and curb gang violence
 - Promote development for at-risk youth
- 23 GRYD Zones throughout LA



(Youth Services Eligibility Tool)

Questionnaire

Questions

Sections

Attitudinal (39 observed)

Do you agree or disagree with these statements? SCALE SHOWCARD 3

neither strongly strongly disagree agree nor agree disagree disagree

It is okay for me to lie (or not tell the truth) if it will keep F21 my friends from getting in trouble with parents, teachers or police.

(5)

SCALE People sometimes break rules or laws. I'd like you to be honest with me about the rules or laws you have broken in your entire life and in the last six months. Remember, your answers will stay private.

Behavioral (17 observed)

Have you ... SHOWCARD 6

a. In the last 6 months

b. EVER c. With gang

IJ40 Used alcohol or cigarettes?

(N)

(4)



YSET

Dataset

1 Data Cleaning Landing to the state of the

32896 observations

22567 participants

~1600 participants in YRR Dataset



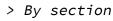


Administrative

nistrative > Date

> By question

> UniqueID



> By concern lv.

> Intake/Retake



Demographic



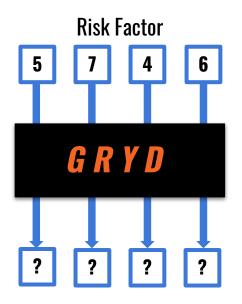
> Ethnicity



- > Eligibility
- > Original RF
- > Reconstructed RF



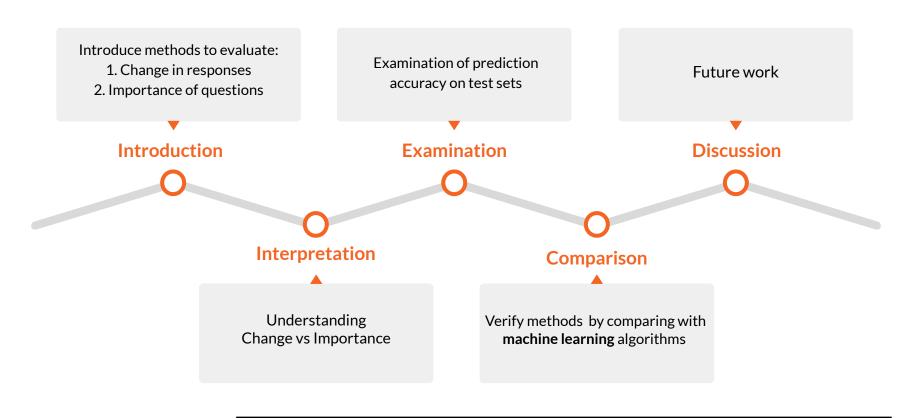
Areas of Interest



- 1. Evaluating the change in responses
- 2. Importance of questions in calculating the risk factor
- 3. Prediction of future "risk variables" (Risk Factor, Eligibility, Concern Levels, etc.)

How effective is the GRYD program?

Agenda



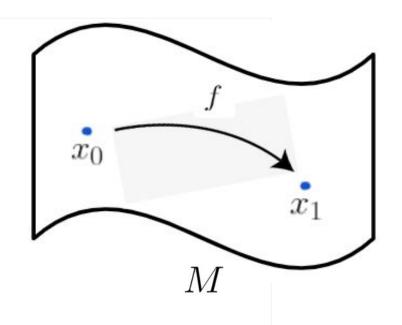
Dynamical System

"Participant points" on manifold:

$$x_k \in M$$

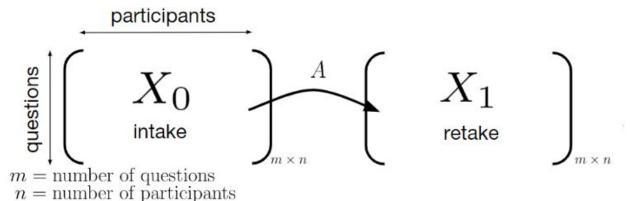
Dynamics of the system:

$$x_{k+1} = f(x_k)$$



Dynamic Mode Decomposition





- 1) Find linear transformation matrix A such that AX_0 approximates X_1 : $||AX_0 X_1||_F = 0$
- 2) Compute the Singular Value Decomposition of X_0 : $X_0 = U\Sigma V^*$
- 3) Compute the transformation matrix A: $A = (X_1)(X_0)^{\frac{1}{4}} = X_1V\Sigma^{-1}U^{\frac{1}{4}}$
- 4) Compute dominant eigenvalues and eigenvectors of A

- Interpretation -

DMD

Results

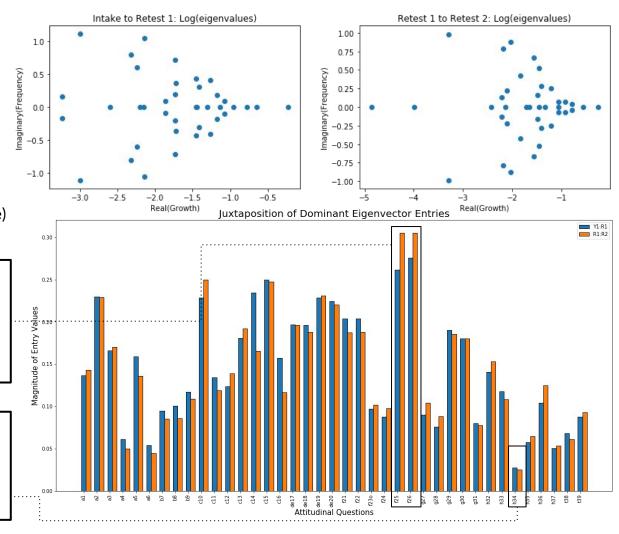
(Questions' susceptibility to change)

F25: It is okay to beat people if they beat me first.F26: It is okay to beat people if I do it to stand up for myself.

are reluctant to change

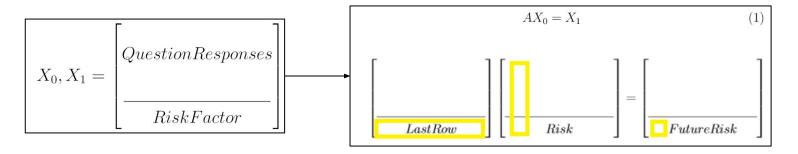
H34: How many of your friends have attacked someone with a weapon

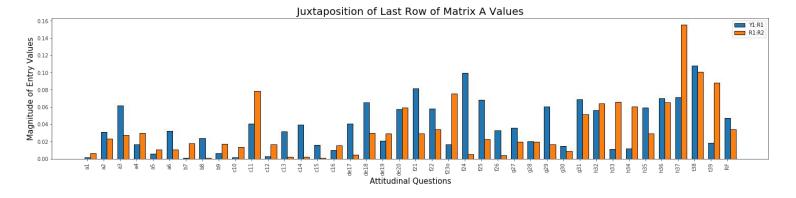
is susceptible to change



Questions' Contributions to Risk Factor

Purpose: Analyze importance of questions in calculating the total risk score of the next program period





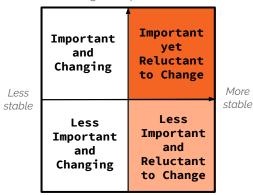
DMD Results

Change

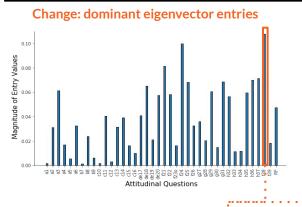
VS.

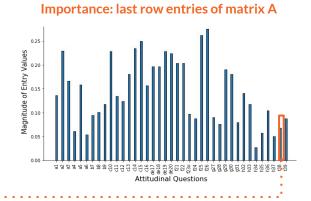
Importance

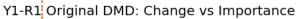
Higher importance

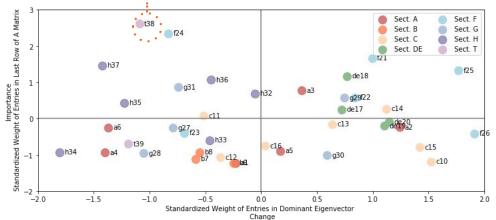


Lower importance





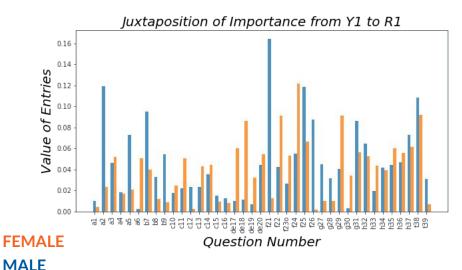


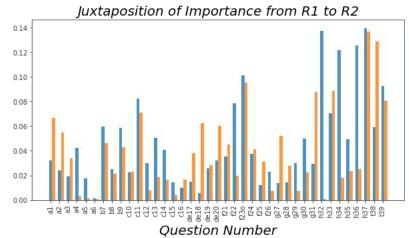


Shortcomings of DMD

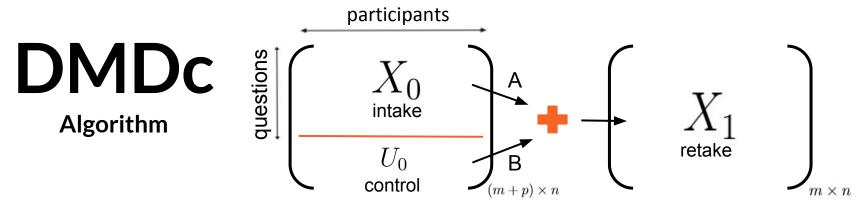
The DMD algorithm does not explain the **variation** in change among different **characteristics** of participants like age and gender, and this issue can be resolved by applying DMD with control (DMDc)

Gender Differences





Dynamic Mode Decomposition + Control



m = number of questions; n = number of participants; p = number of control levels

- 1) Find transformation matrices A and B such that $(AX_0 + Bu_0)$ approximates X_1 : $||AX_0 + Bu_0 X_1||_{E} = 0$
- 2) Compute Singular Value Decomposition of X₀: X₀ = U∑V*
- 3) Then compute for transition matrix $A = X_1 V \Sigma^{-1} U_A^*$, and $B = X_1 V \Sigma^{-1} U_B^*$, where U_A is the first m rows of U, and U_B is the last p rows of U
- 4) Make predictions using X₁ = AX₀ + Bu₀

Control Variables

Gender



- Male
- Female

Ethnicity



- African-American
- Asian
- Hispanic
- White
- Other

District



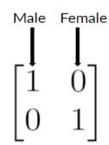
• 23 GRYD Zones

Age



• 10-16 years old

Control matrices created using one-hot encoding:

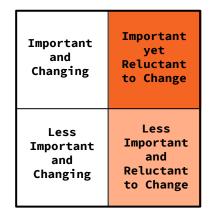


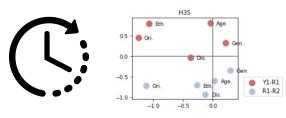
E.g. (for gender)

DMD & DMDc

Change vs. Importance

What we have learned...





> Questions' importance typically
change over time



> Different questions have
different effects
according to demographic
groups

> Effects are shown in results of models with different controls

For all participants, GRYD should put more emphasis in areas of:

Section C

Critical Life Events

Section H

Peer Delinquency

Section DE

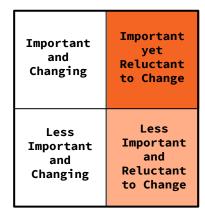
Impulsive Risk Taking

Section T

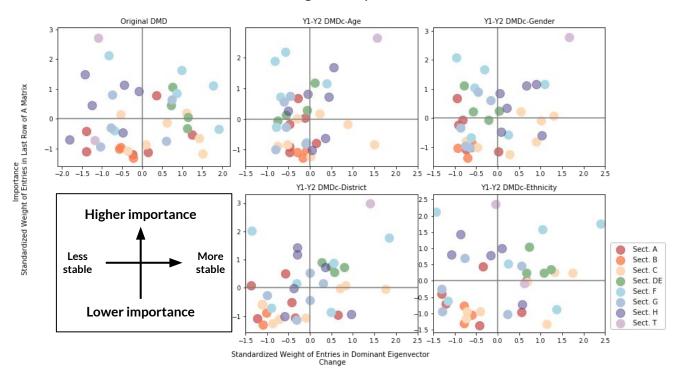
Family Gang Influence

Change

Importance



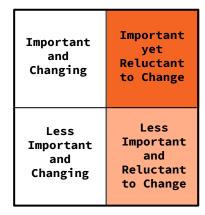
Y1-R1: Change vs Importance



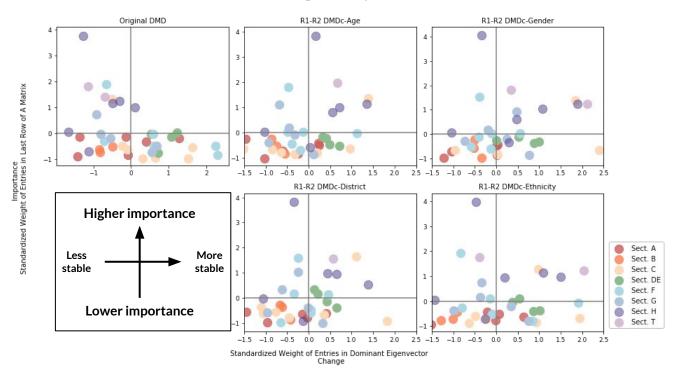
Change

VS.

Importance



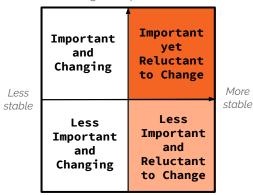
R1-R2: Change vs Importance



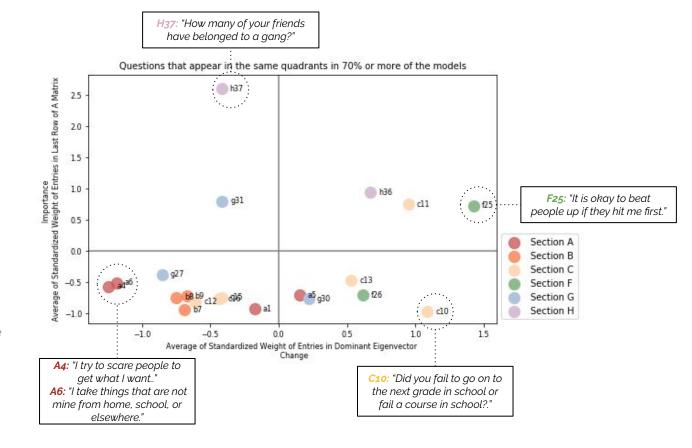
Change vs. Importance

Questions that consistently appear in the **same quadrants** across models

Higher importance



Lower importance

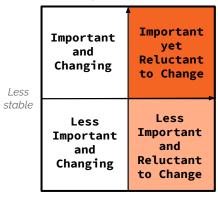


Change

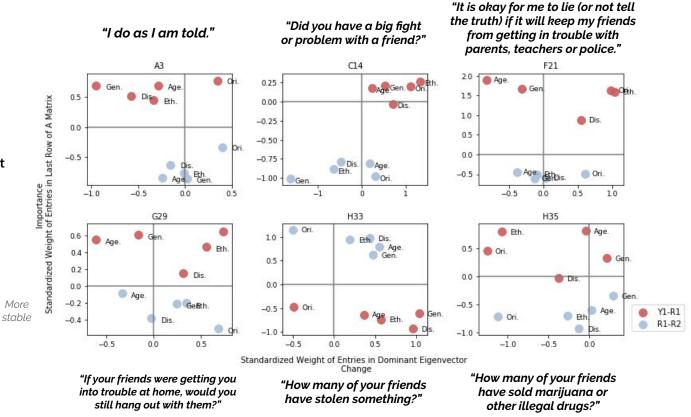
vs.
Importance

Questions that appear in **different quadrants** in different models

Higher importance



Lower importance



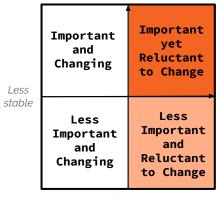
Change

VS.

Importance

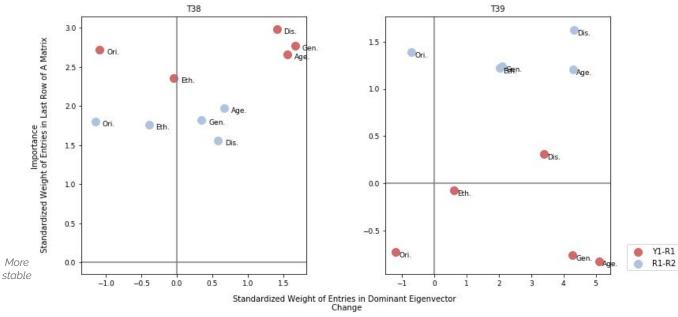
Section TFamily Gang Influence

Higher importance



Lower importance

Change vs Importance for Section T Across Models



"How many people in your family think that you will join a gang?"

"How many people in your family are gang members?"

Error Minimization Properties

DMD

Lemma 1: Let X be a $k \times n$ matrix, and Y another $m \times n$ matrix, then the matrix $A \in \mathbb{C}^{m \times k}$ that minimizes the functional $g(A) = ||AX - Y||_2^2$ is given by the solution of the normal equations $AXX^* = YX^*$.

Lemma 2: $A = YX^{\dagger}$ is a solution to the equation $AXX^* = YX^*$.

DMDc

Lemma 3: Let X_{k+1} a real, $m \times n$ matrix, X_k another real $j \times n$ matrix, and u_k a $k \times n$, matrix be given, let Y to be the $(j+k) \times n$ matrix by appending u_k to X_k , then there exists some $M \in \mathbb{C}^{m \times (j+k)}$ the solution to $MYY^* = X_{k+1}Y^*$ of the matrix $A \in \mathbb{C}^{m \times j}$ and the matrix $B \in \mathbb{C}^{m \times k}$ that minimizes the functional $g(x) = ||X_{k+1} - AX_k - Bu_k||_2^2$ are given by the first j columns of M and last k columns of M, respectively.

DMD & DMDc

Prediction Accuracy

Randomly split data into 80% training and 20% testing

Run t-test against DMD to demonstrate the significant increase in precision.

DMDc on <u>district</u> has the smallest MSE

DMD (No Control)			
Trial	MSE (Test)	MSE (Whole)	
1	0.1018	0.0965	
2	0.1004	0.0964	
3	0.1012	0.0964	
4	0.1006	0.0964	
5	0.0993	0.0964	

DMDc (Age)		
Trial	MSE (Test)	MSE (Whole)
1	0.0981	0.0948
2	0.0983	0.0949
3	0.1025	0.0949
4	0.1009	0.0950
5	0.1020	0.0950

	DMDc (District)		
Trial	MSE (Test)	MSE (Whole)	
1	0.0988	0.0924	
2	0.1009	0.0924	
3	0.1007	0.0924	
4	0.1028	0.0923	
5	0.1019	0.0924	

MSE (Whole) 0.0957

0.0956

0.0956 0.0956 0.0956

DMDc (Ethnicity)				DMDc (Ge	nder)
Trial	MSE (Test)	MSE (Whole)	Trial	MSE (Test)	MSE
1	0.0990	0.0956	1	0.1027	0
2	0.1030	0.0956	2	0.1014	0
3	0.1028	0.0957	3	0.1007	0
4	0.0995	0.0957	4	0.0999	0
5	0.1025	0.0957	5	0.0988	0

Table 2. MSE of DMD and DMDc trials

DMD and DMDc (Age)			
MSE	t statistic	p value	
Test	4.1337	0.0001	
Whole	232.4665	0.0000	

DMD and DMDc (District)			
MSE	t statistic	p value	
Test	6.9643	0.0000	
Whole	403.1224	0.0000	

DMD and DMDc (Ethnicity)			
MSE	t statistic	p value	
test	0.4925	0.6229	
Whole	121.0410	0.0000	

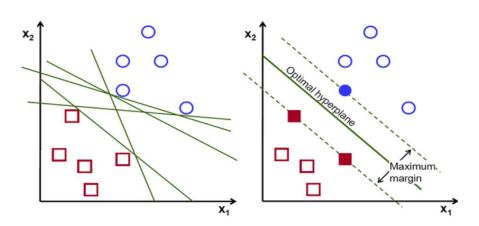
DMD and DMDc (Gender)			
MSE t statistic p value			
Test	4.4854	0.0000	
Whole	148.0830	0.0000	

Table 3. t-test of DMD and DMDc

Confirmation of DMD via Machine Learning

using SVM + DT

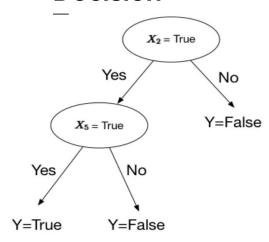
Support Vector Machine (SVM)



$$\min_{\mathbf{w}, \xi, \rho} \frac{1}{2} \mathbf{w}^T \mathbf{w} + \sum_{i=1}^n C_i \xi_i$$

subject to $y_i(\mathbf{w}^T \phi(\mathbf{x}_i) + \rho) \ge 1 - \xi_i,$ $i = 1, \dots, n$
 $\xi_i \ge 0,$ $i = 1, \dots, n$

Decision

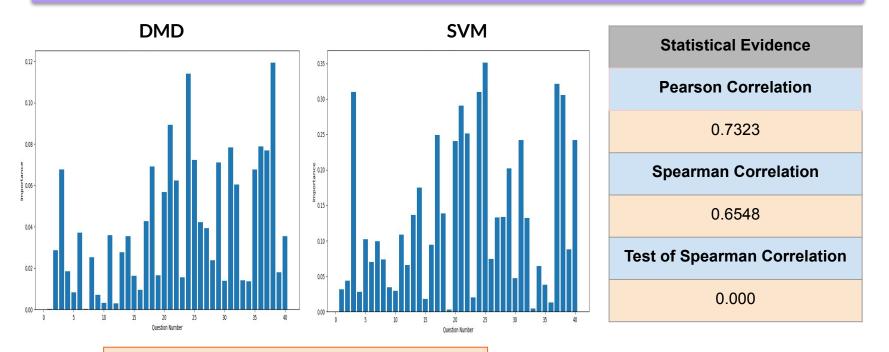


Key Concepts:

- Entropy Loss
- $E(S) = \sum_{i=1}^{c} -p_i \log_2 p_i$

Confirmation of Question Importance

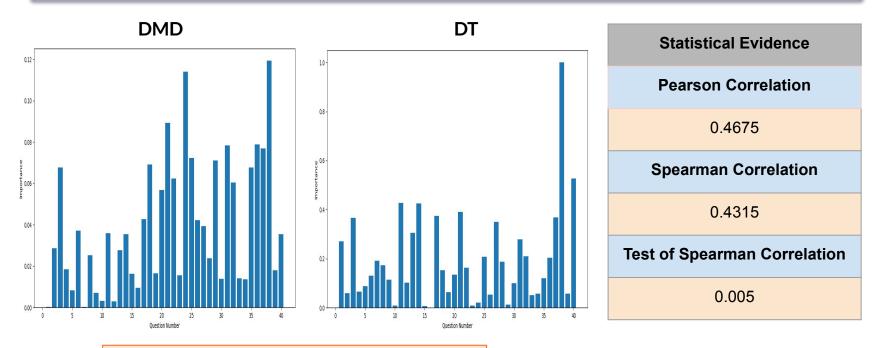
DMD vs SVM



Question Importance from DMD and SVM

Null hypothesis: results for the two models are uncorrelated

Confirmation of Question Importance



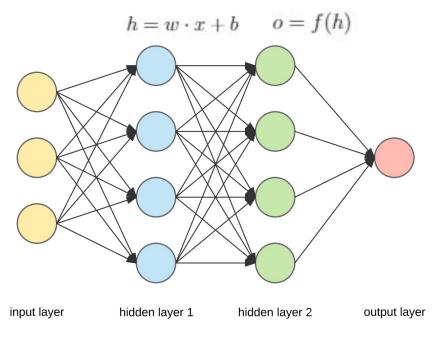
Question Importance from DMD and DT

Null hypothesis: results for the two models are uncorrelated

Future Work

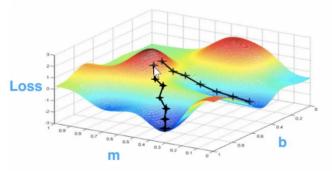
- Explore the relationship between DMD algorithm and neural networks
- 2. Find a criterion for detecting the dropout group from the program
- 3. Try develop a modified version of DMD which take partial label information

ANN and Gradient Descent



Basic Structure of Artificial Neural Network





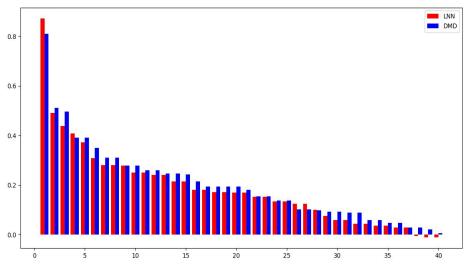
Adam:

An algorithm that is widely used in stochastic optimization problem in Neural Network

AdaGrad:

An adaptive gradient method used in optimization problem

Comparison of DMD and LNN

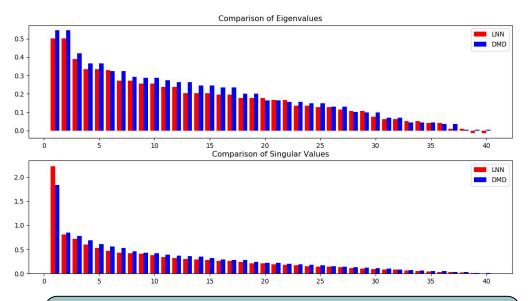


	DMD		LN	LNN	
	Test	Whole	Test	Whole	
Trial 1	0.1007	0.0965	0.1000	0.0966	
Trial 2	0.1010	0.0964	0.1007	0.0968	
Trial 3	0.1004	0.0964	0.1011	0.0967	
Mean	0.1013	0.0964	0.1018	0.0975	
S.D.	0.0017	0.0004	0.0020	0.0005	

Comparison of Eigenvalues
Correlation Coefficient = 0.9988

Comparison of MSE

Comparison of DMDc and LNNc



	DMDc		LN	Nc
	Test	Whole	Test	Whole
Trial 1	0.0987	0.0956	0.1004	0.0962
Trial 2	0.0996	0.0956	0.1008	0.0965
Trial 3	0.0984	0.0956	0.1011	0.0972
Mean	0.1010	0.0956	0.1016	0.0968
S.D.	0.0018	0.0005	0.0020	0.0008

Comparison of Eigenvalues and Singular Values Correlation Coefficient (Eigenvalues) = 0.9927 Correlation Coefficient (Singular Values) = 0.9864

Comparison of MSE

Discussion of the Theoretical Lowest Error Bound

Objective Function of DMD:

 $X_{k+1} = AX_k$

Objective Function of LNN(c):

 $X_{k+1} = AX_k + b$

Objective Function of DMDc:

$$X_{k+1} = AX_k + Bu_k$$





Optimization Problem of DMD:

$$L_1 = \min_{A} ||x_{k+1} - Ax_k||_2$$

Optimization Problem of LNN(c):

$$L_2 = \min_{A,b} ||x_{k+1} - Ax_k - b||_2$$

Optimization Problem of DMDc:

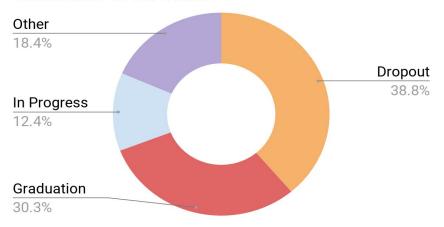
$$L_3 = \min_{A,B} ||x_{k+1} - Ax_k - Bu_k||_2$$

Relationship of Lowest Error Bound of Three Methods:

Future Work

Distinguishing Dropouts

Distribution of the Status



Possible Reasons

Long Term
Non-Attendance

Refuse Service

	SVM	Random Forest
Acc.	85.89%	89.42%

Summary of Program Dropout			
Number of Participants	22548		
Participants with Status 13549			
Number of Dropouts	5258		
Dropouts after Y1	4110		
Dropouts after R1	922		
Dropouts after R2	226		

Future Direction:

- Interpretable rules of how to determine whether participant will dropout
- Metrics describing the probability of dropout

Recap

DMD

 Used to observe change in question responses & their contribution in calculating risk factor

DMDc

- Used to make these same observations as DMD, however includes control variable
 - Has a <u>higher prediction</u> accuracy than DMD

Confirmed DMD/DMDc algorithm via machine learning

 SVM and Decision Tree provide <u>correlated</u> results of question importances

Question scores are **decaying** over time.

GRYD should focus on questions that are important, but reluctant to change.

(Critical Life Events, Impulsive Risk Taking, Peer Delinquency, and Family Gang Influence)

Also we need to take into account demographic groups because they do have an effect on question responses.



Thanks for listening!

Special Thanks to:

Professor Jeffrey Brantingham and Professor Andrea Bertozzi

Questions?