IFT 6758 Final Project

Final Project Presentation

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Team: User13 (Tempête De Données)

Team Members:

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Scoreboard

How we beat all the baselines!

AGE	GENDER	OPN	NEU	EXT	AGR	CON
0.621	0.827	0.639	0.790	0.780	0.651	0.713

Problem Statement

User modeling with multi-source user data such as text, images, and relations to arrive at accurate user profiles.

Prediction Task Overview

Classification Tasks

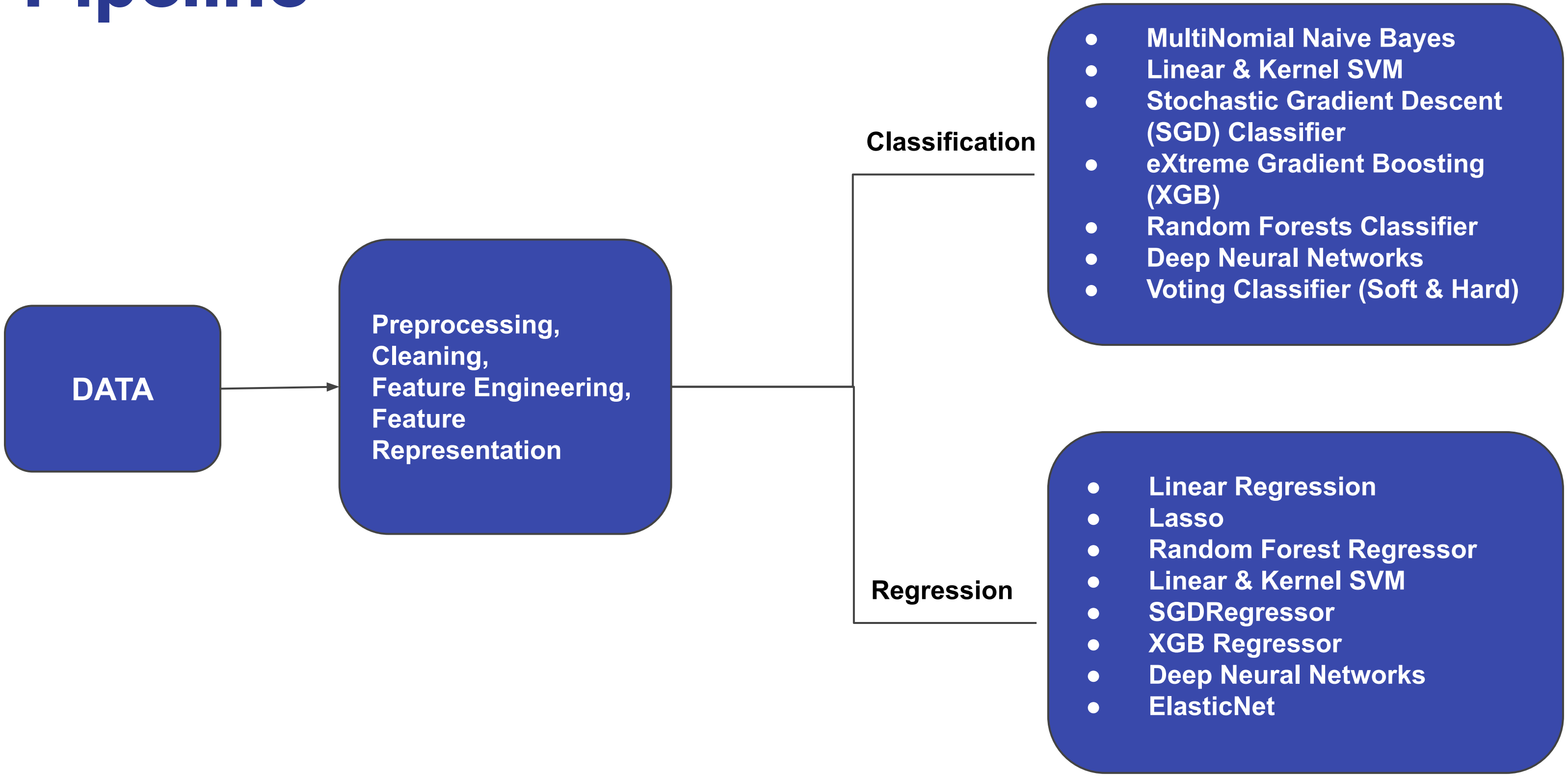
- Categorical age
- Gender

Regression Tasks

Régression Task:

- Personality Score Prediction
    - Openness
    - Conscientiousness
    - Extroversion
    - Agreeableness
    - Neuroticism

Pipeline


DATA
Preprocessing,
Cleaning,
Feature Engineering,
Feature
Representation
Classification
MultiNomial Naive Bayes
Linear & Kernel SVM
Stochastic Gradient Descent (SGD) Classifier
eXtreme Gradient Boosting (XGB)
Random Forests Classifier
Deep Neural Networks
Voting Classifier (Soft & Hard)
Regression
Linear Regression
Lasso
Random Forest Regressor
Linear & Kernel SVM
SGDRegressor
XGB Regressor
Deep Neural Networks
ElasticNet

Feature Analysis

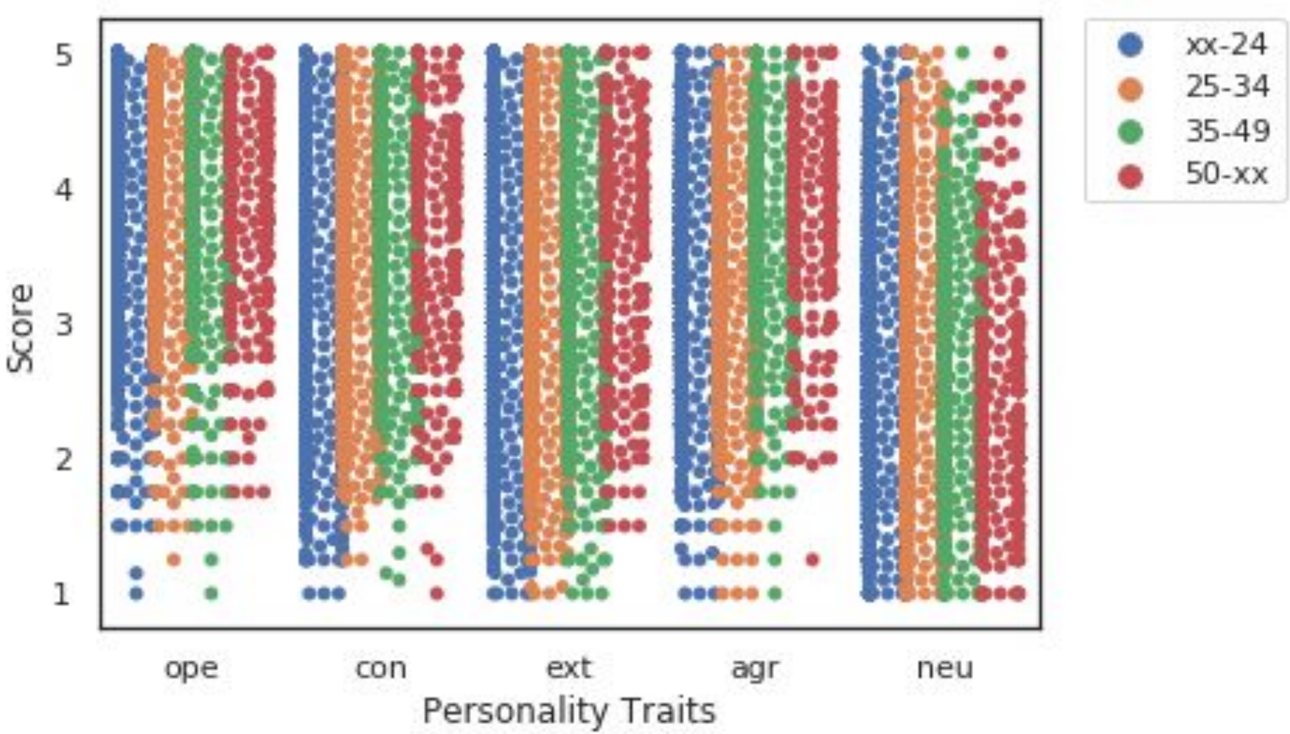
Features

1. Text: LIWC + NRC
2. Image: Oxford features
3. Graph: Users' page likes

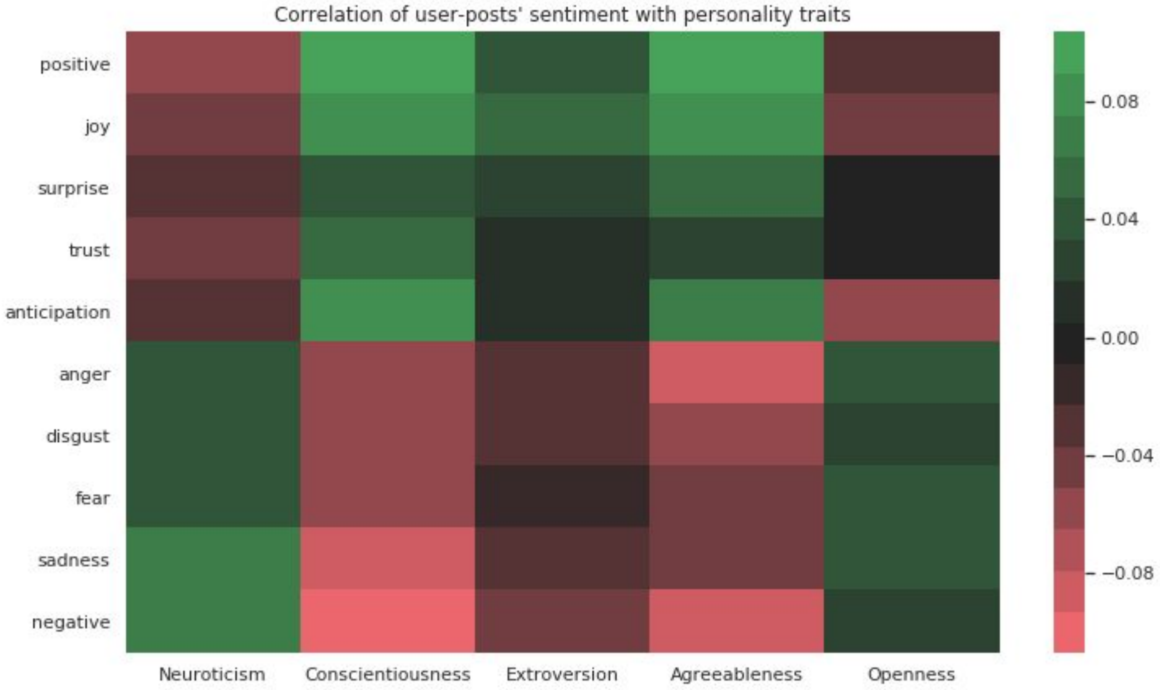
Feature Statistics

- Number of users: 9500
- Total number of features: 65 (oxford) + 1 (relationships) + 81 (liwc) + 10 (nrc)
- Missing images for 2326 users
- Multiple faces in images of ~700 users

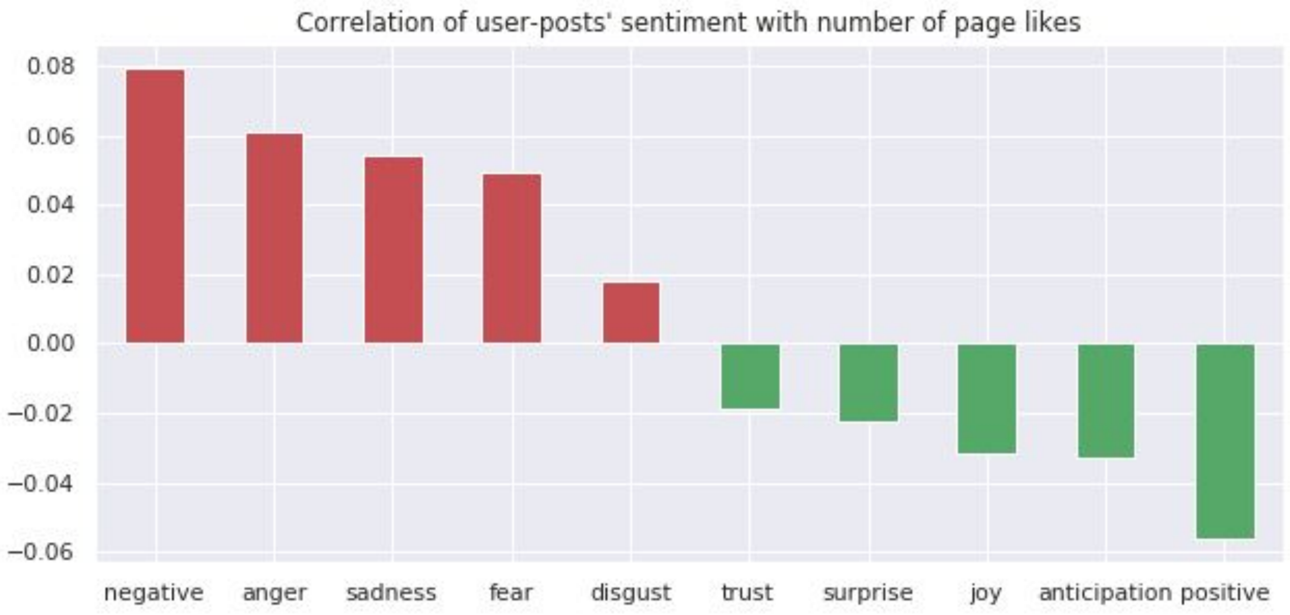
Personality vs Age



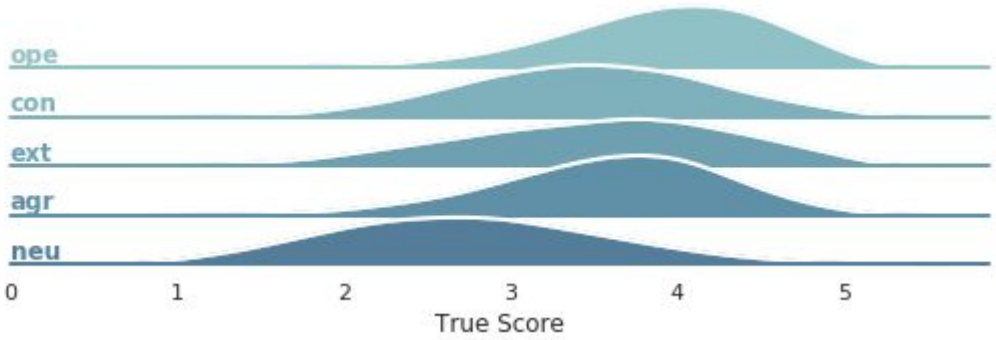
Personality vs User Posts

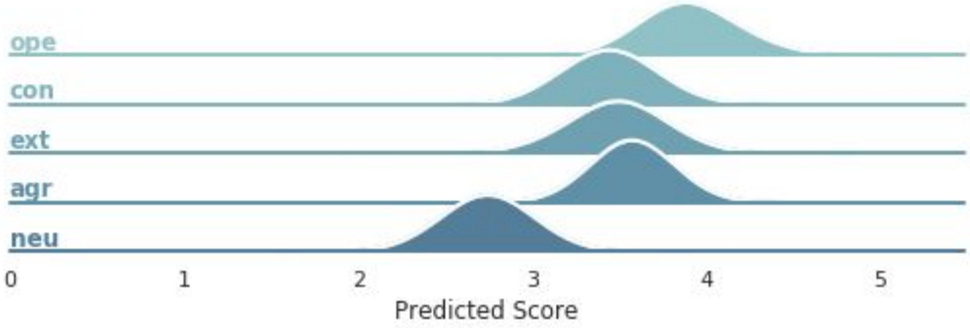


Page Likes vs User Posts

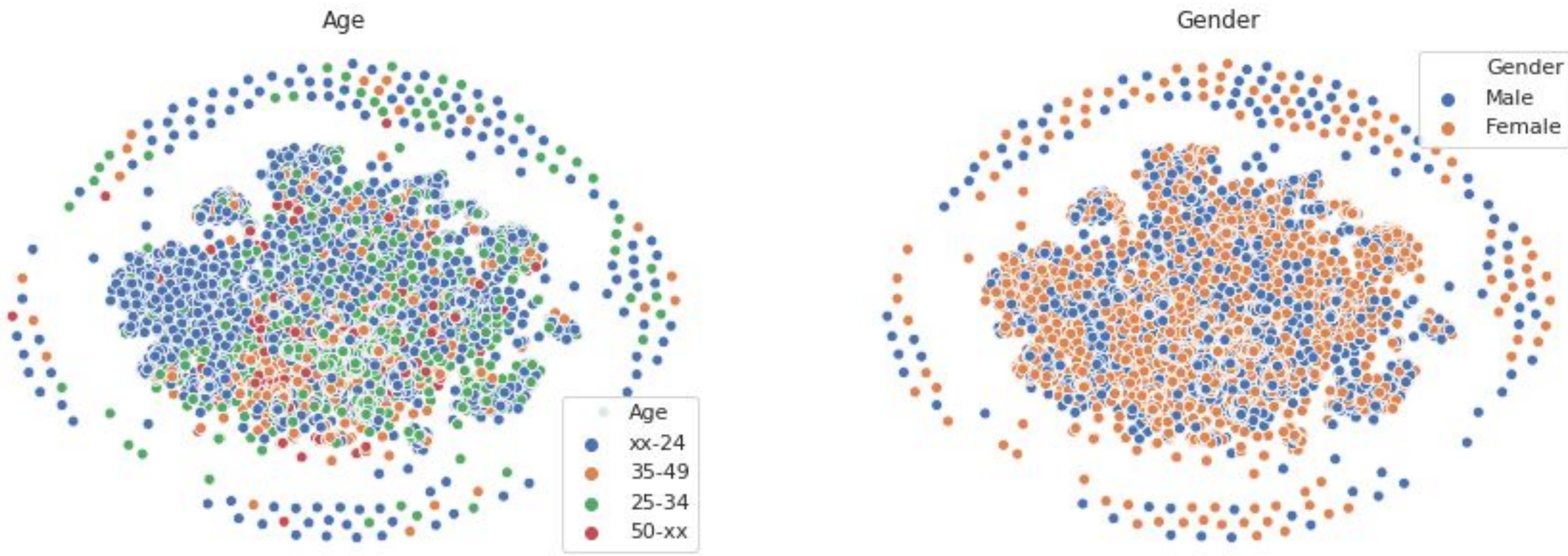


Personality Prediction Analysis

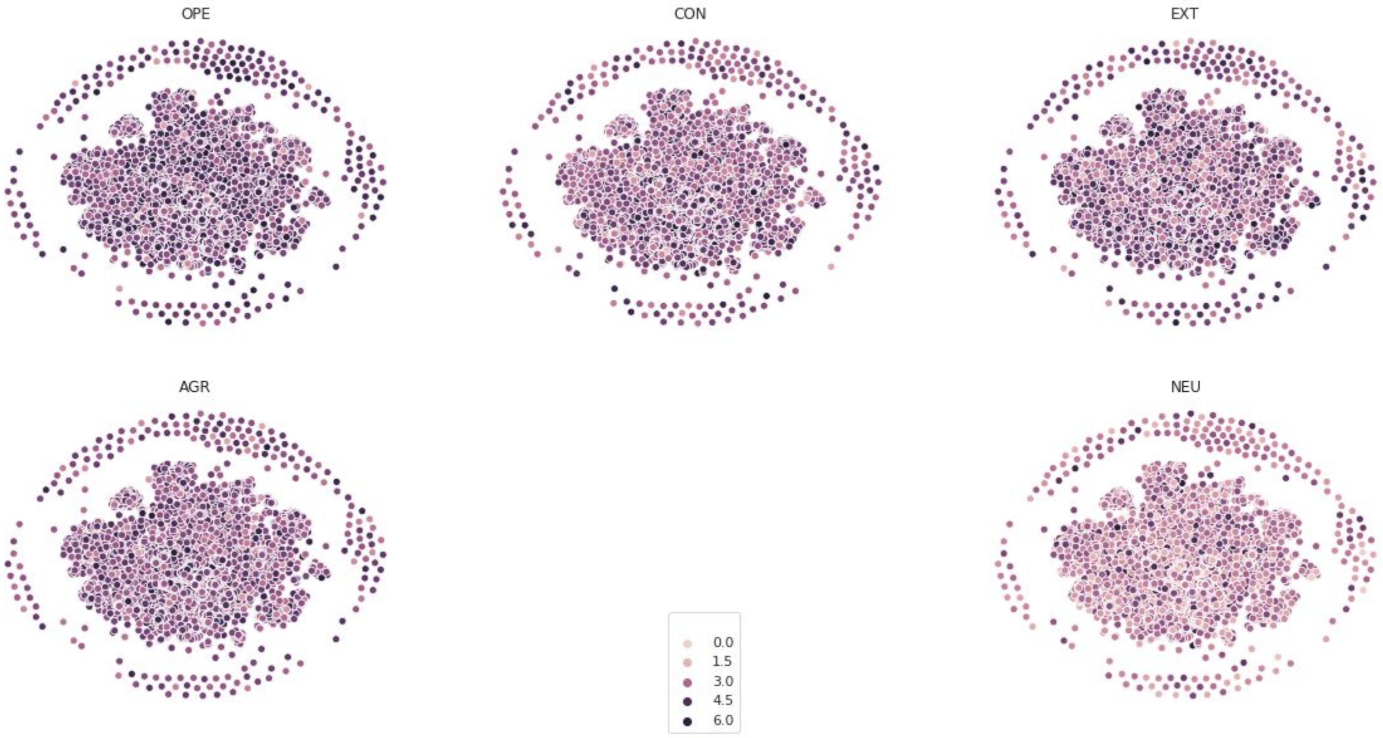




Node2Vec Classification

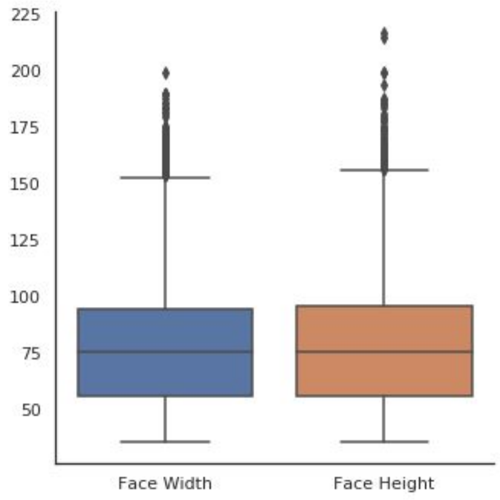


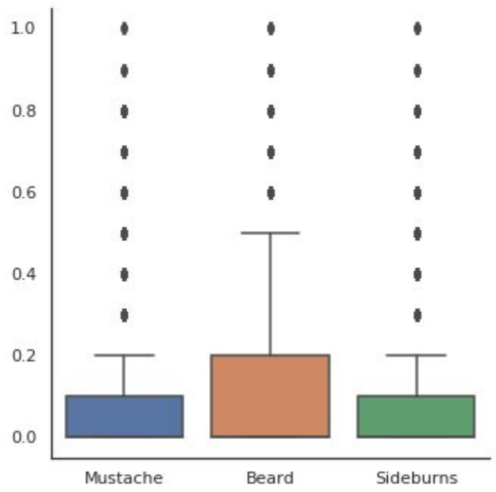
Node2Vec Regression



Feature Preprocessing

- Removed Outliers (using IQR)
- Scaling: Min-Max/Standard Scaling





Feature Selection

- Using Filter-based methods (SelectKBest)
- Using Embedded feature selection methods (Lasso LR and RandomForest)
- Important features identified:

FACIAL	LIWC	NRC
facialHair_mustache	ipron	negative
facialHair_beard	swear	anger
facialHair_sideburns	social	disgust
faceRectangle_width	negemo	fear
faceRectangle_height	feel	joy

Feature Engineering

- Merged facial features such as facial hair
- Converted raw facial coordinates into lengths and areas
- Created node embeddings for users based on page likes, text, and facial features

Feature Representation

Relation feature representation

- **Relations**
  - Multi-one hot encoding
  - Like-Frequency Inverse User Frequency (similar to tf-idf)
  - Weighted and Unweighted Node2vec

Multi-one hot encoding

- Creates sparse matrix containing user and likes
- Experimented with shortlisting pages with different thresholds: **0, 5, 10, 25**
- Converted data into a multi-one hot encoding.

	Page 1	Page 2	Page 3	Page 4
User 1	1	0	1	1
User 2	0	0	1	0
User 3	1	0	0	1

Like-Frequency Inverse User Frequency

- Creates sparse user-like matrix
- Experimented with shortlisting pages with different thresholds: **0, 5, 10, 25**
- Converted data into a multi hot encoding using approach similar to tfidf.

	Page 1	**Page 2**	**Page 3**	**Page 4**
User 1	0.25	0	0.2	0.4
User 2	0	0	0.4	0
User 3	0.25	0	0	0.2

Node2vec

- Optimize embeddings with biased random walks, using word2vec skip-gram model
- Learn low dimensional latent representations by projecting users and other entities as graph

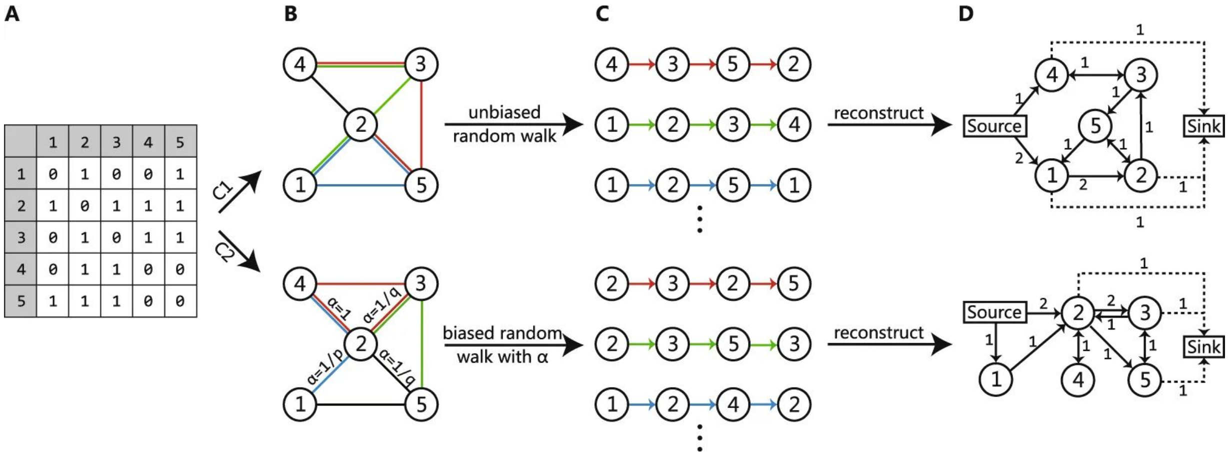
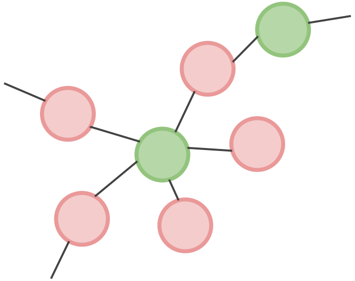
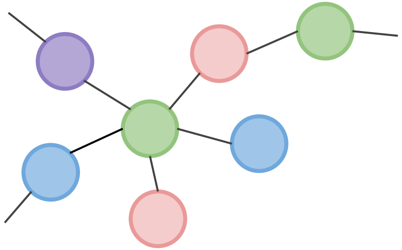


Image: https://www.nature.com/articles/s41598-017-12586-y

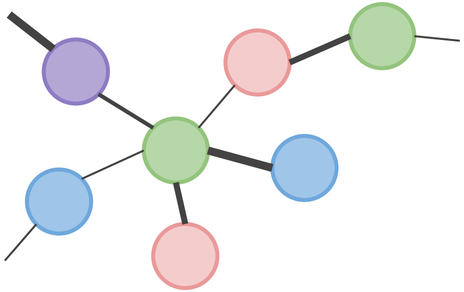
Node2vec Heterogeneous Graph Formation



(Un)-Weighted Graph
With only 2 types of nodes



(Un)-Weighted Graph
With multiple types of nodes



Weighted Graph

- With multiple types of nodes
- Page weights were assigned using tfidf kind of approach
- Improve weight to pages with less number of likes

Legend:

- Users
- Pages
- Selected Facial Features
- Selected Text Features

Embedding dimension - 128
Number of walks - 10, 20
Walk length - 50, 60, 80
Return hyperparameter - 0.75, 0.8, 0.9, 1
Inout hyperparameter - 0.9, 1.0
Context window size - 10
Number of iterations - 1, 2, 5

Experimented Methods

Approach 1

Using Individual Data Sources

Train all data sources individually for each task to find the best algorithm

Classification Tasks Evaluation

	Classification Accuracy							
	Gender				Âge			
Baseline	0.594				0.591			
Features Used	**Oxford**	**Text**	**N2v**	**Page Likes**	**Oxford**	**Text**	**N2V**	**Page Likes**
Random Forests	80.00	54.10	56.26	77.80	59.91	50.11	61.79	62.50
Linear SVM	68.11	55.10	56.05	78.50	61.47	61.47	61.79	**67.56**
MNB	71.9	44.15	-	54.61	-	53.17	-	60.15
lightGBM	80.17	55.67	55.18	76.83	60.78	61.43	61.17	62.79
XGB	**81.08**	55.10	55.89	77.36	61.50	62.60	61.32	63.40

Regression Tasks Evaluation (1/2)

		RMSE				
Algorithms	**Features Used**	**OPN**	**NEU**	**EXT**	**AGR**	**CON**
Linear Regression (Ridge/Elastic Net)	**Oxford**	0.634	**0.769**	0.819	0.669	0.726
	Text	0.626	0.776	0.778	0.651	0.707
	Page Likes	-	-	-	-	-
	N2v	0.596	0.7782	0.7697	0.6492	0.703
Linear Regression Lasso (L1)	**Oxford**	0.634	0.769	0.819	0.669	0.726
	Text	0.625	0.775	0.778	0.648	0.705
	Page Likes	-	-	-	-	-
	N2v	**0.5963**	0.7787	**0.7702**	**0.6479**	**0.7029**

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Regression Tasks Evaluation (2/2)

		RMSE				
Algorithms	**Features Used**	**OPN**	**NEU**	**EXT**	**AGR**	**CON**
Random Forests	**Oxford**	0.638	0.782	0.831	0.673	0.736
	Text	0.627	0.780	0.779	0.653	0.710
	Page Likes	0.621	0.778	0.80	**0.64**	0.71
	N2v	0.6082	0.7866	0.7889	0.6527	0.713
XGB Regressor	**Oxford**	0.631	**0.768**	0.823	0.665	0.728
	Text	0.623	0.778	**0.778**	0.648	**0.701**
	Page Likes	0.621	0.773	0.791	0.65	0.712
	N2v	**0.609**	0.781	0.787	0.652	0.708

Approach 1

What worked - In a nutshell

Best Results

Gender Classification
Oxford Features using XGB

Age Classification
LIWC Features using XGB

Personality Prediction
LIWC Features using XGB

Approach 2

Multi Modal Fusion

Stack data sources for each task to find the best algorithm

Model Agnostic Approaches

Model-free approaches

- Early Fusion
- Late Fusion
- Hybrid Fusion

Multi Modal Fusion

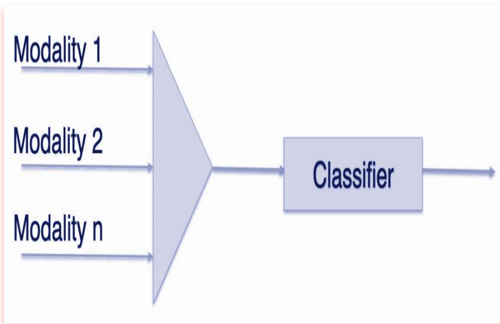
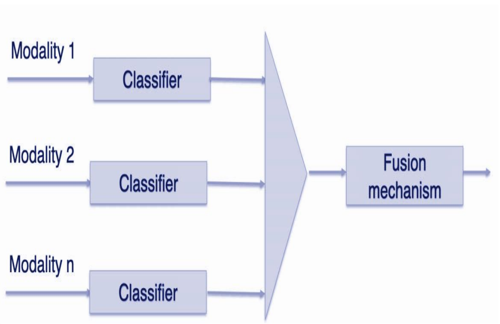
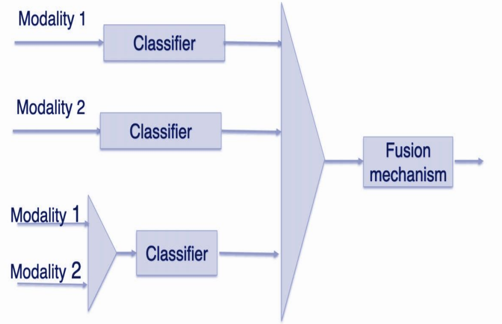
Early Fusion	Late Fusion	Hybrid Fusion
		
● In this approach, we implement feature concatenation. ● It helps exploit feature dependencies.	● In this approach, we train both unimodal and multimodal fusion predictors. ● Fusion mechanism tried was voting.	● In this approach, we combine both early and late fusion mechanisms.

Image: https://ift6758.github.io/lectures/multimodal_learning.pdf

Classification Tasks Evaluation

	Classification Accuracy							
	Gender				Âge			
Features Used	Oxford + Text EARLY FUSION	Oxford + N2V EARLY FUSION	Oxford + Text + N2V EARLY FUSION	Oxford + Text + Occurrence Matrix LATE FUSION	Oxford + Text EARLY FUSION	Oxford + N2V EARLY FUSION	Oxford + Text + N2V EARLY FUSION	Oxford + Text + Occurrence Matrix LATE FUSION
Random Forests	83.11	84.368	84.526	82.13	61.947	61.947	62.684	61.11
Linear SVM	79.79	85.526	**85.684**	84.123	61.526	**71.368**	70.842	70.66
lightGBM	82.89	84.00	85.105	83.87	62.632	65.632	67.158	68.19
XGB	83.74	84.94	86.316	85.178	63.316	67.474	68.632	68.66

Regression Tasks Evaluation (1/2)

Algorithms	Features Used	Fusion Techniques	OPN	NEU	EXT	AGR	CON
Linear Regression	Oxford + Text	EARLY FUSION	0.633	0.790	0.814	0.659	0.708
	Oxford + N2V	EARLY FUSION	0.602	0.780	0.779	0.642	0.704
	Oxford + Co-Occurrence Matrix	LATE FUSION	0.612	0.782	0.789	0.652	0.709
	Oxford +Text +N2V	EARLY FUSION	0.613	0.780	0.780	0.645	0.707
	Oxford + Text + CO-Occurrence Matrix	LATE FUSION	0.607	0.788	0.781	0.648	0.705
Lasso (L1)	Oxford + Text	EARLY FUSION	0.631	0.791	0.804	0.656	0.716
	Oxford + N2V	EARLY FUSION	0.600	0.780	0.769	0.640	0.700
	Oxford +Text +N2V	EARLY FUSION	0.599	0.779	0.764	0.638	0.697
	Oxford + Text + CO-Occurrence Matrix	LATE FUSION	0.605	0.782	0.785	0.644	0.709

Regression Tasks Evaluation (2/2)

			RMSE				
Algorithms	Features Used	Fusion Technique	OPN	NEU	EXT	AGR	CON
Random Forests	Oxford + N2V	EARLY FUSION	0.611	0.785	0.783	0.649	0.710
	Oxford + Text + N2V	EARLY FUSION	0.609	0.689	0.779	0.644	0.703
XGB Regressor	Oxford + Text	EARLY FUSION	0.618	0.785	0.792	0.650	0.701
	Oxford + N2V	EARLY FUSION	0.611	0.786	0.779	0.646	0.707
	Oxford + Text + N2V	EARLY FUSION	0.609	0.777	0.7877	0.641	0.702

Best Results

Gender Classification
Oxford Features + Node2Vec Relation Features using SVM

Age Classification
Oxford Features + Text + Node2Vec Relation Features using SVM

Personality Prediction
Did not improve results with multiple data sources

Approach 3

Multi Modal Fusion

Stacking predictions as input to predict other tasks

Using predictions as features

Using previous predictions like gender, age as input to predict other tasks.

X	y1
x1	0
x2	1
x3	0

Classifier 1

X	y1	y2
x1	0	1
x2	1	0
x3	0	1

Classifier 2

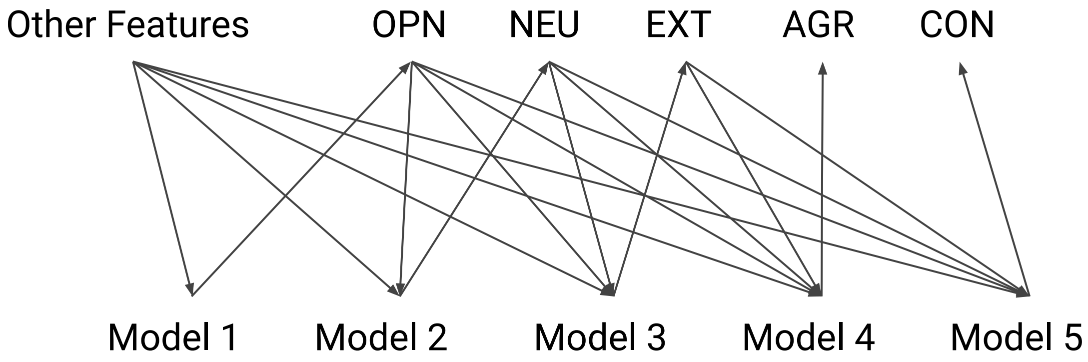
X	y1	y2	y3
x1	0	1	1
x2	1	0	0
x3	0	1	0

Classifier 3

X	y1	y2	y3	y4
x1	0	1	1	0
x2	1	0	0	0
x3	0	1	0	0

Classifier 4

Regressor Chaining



What Next? Approach 4

Combining all the approaches

Stack models built on individual data source, multiple data sources and train using classifier/regression chaining at all levels.