

CORONAVIRUS AND MENTAL HEALTH

How are you, really?





01

PROBLEM STATEMENT

Stakeholders, context, success metrics

02

METHODOLOGY

Brief overview of workflow

03

DATA ANALYSIS

Data cleaning and EDA

04

MODEL PREPARATION

Feature engineering, feature selection

05

MODEL OPTIMIZATION

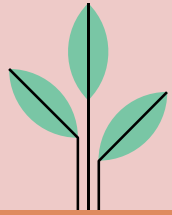
Optimization of supervised machine learning models(kNN, Neural Nets, Logistic regression, RandomForests)

06

CONCLUSION

Addressing the advantages, shortcomings of models and recommendations

CONTENT

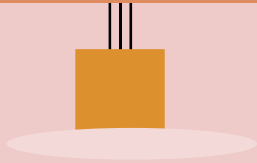


In addition to the economical and social effects of the pandemic on the livelihoods of people, it has also brought to light the implications of such an unprecedented pandemic on the mental health of people.

Large scale disasters (SARS,9/11,hurricanes)) were almost always accompanied with increase in mental health and behavioural disorders

Together with past knowledge and existing data, what can we do to prevent such occurrences?

INTRODUCTION



Goal:

Aim to identify characteristics of respondents prone to developing avoidance behaviours in receiving mental health aid and build a binary classification model to predict likelihood of this tendency based on data from **Household Pulse Survey**. Models are evaluated using **ROC-AUC** and **recall** scores

Stakeholders:

Mental Health America, Local healthcare departments



PROBLEM STATEMENT

1.

2.

3.

4.

Business Goal

- Develop a binary model to identify vulnerable respondents that exemplifies resistance to receiving mental health aid

Data Cleaning

- Presence of imbalanced classes in target variable
- Presence of null values
- Presence of correlated predictor variables

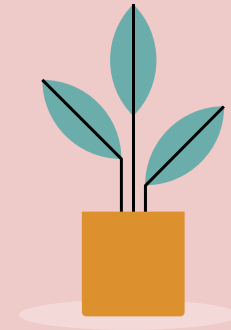
Model Pre-processing

- Feature selection
- Feature engineering (creating new feature, PCA)
- Remove correlated categorical features (Pearson's chi squared test)

Data Modeling

- Experimenting with different models
- Logreg, Xgboost, k-NN, RandomForest, Neural Nets)

METHODOLOGY





HOUSEHOLD PULSE SURVEY

Time period: 19 Aug - 19
Sep)

Rows: 219,070

Columns: 188

DATA ANALYSIS

	T_BIRTHYEAR	INSURED	WKRLOSS	FOODSUF	MH_NOTGET
1	1989	Yes	Yes	Somewhat confident	No
2	1988	Yes	No	Very confident	No
3	1969	No	Yes	Not at all confident	Yes
4	1947	Yes	No	-	-



IMPUTATION

- Impute missing values with averages
- Remove missing values



FEATURE ENGINEERING

- Creation of new feature ('HOUSEPAY') to reduce dependence between predictor variables
- PCA for dimensionality reduction



DROPPING REDUNDANT FEATURES

- Remove secondary features (travel plans, accessibility to internet etc)



FEATURE SELECTION

- Pearson's Chi Squared test to analyze correlation between categorical variables and target variable
- Reduce unrelated/redundant features($p\text{-value} > 0.05$)

DATA CLEANING

TRAIN -TEST SPLIT

Splitting final data into
train and test sets

STANDARD SCALING

Scaling X_{train} and X_{test}
for algorithms that use
distance metrics(k-NN) and
gradient descent(Neural
Nets)


UNDER - SAMPLING


Undersampling of majority
classes in train set using
RandomUnderSampler to
balance dataset


MODEL PREPARATION


Bimodel strategy


Logistic Regression

 Inference: Identify and quantify feature importance


 Hyperparameters:
C:0.001, penalty: L2


 Recall: 0.802
ROC-AUC: 0.790

 Pros: Rank feature importance, fast


 Cons: Assume linear relationship, lower recall score

ExtraTrees Classifier

 Prediction: Generate accurate predictions

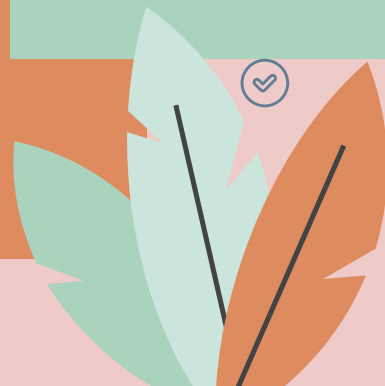
 Hyperparameters:
class_weight: balanced,max_depth: 40,
max_features: auto, min_samples_leaf: 40

 Recall: 0.856
ROC-AUC: 0.770

 Pros: Good balance of bias-variance trade off

 Cons: Slow implementation

MODEL OPTIMIZATION



Logistic Regression

Top 10 predictor features



FEATURE
IMPORTANCE

Logistic Regression

1

DOWN :
How often do you feel
sad/hopeless?
1 - Not at all, 4 - Everyday

2

ANXIOUS :
How often do you feel
anxious?
1 - Not at all, 4 - Everyday

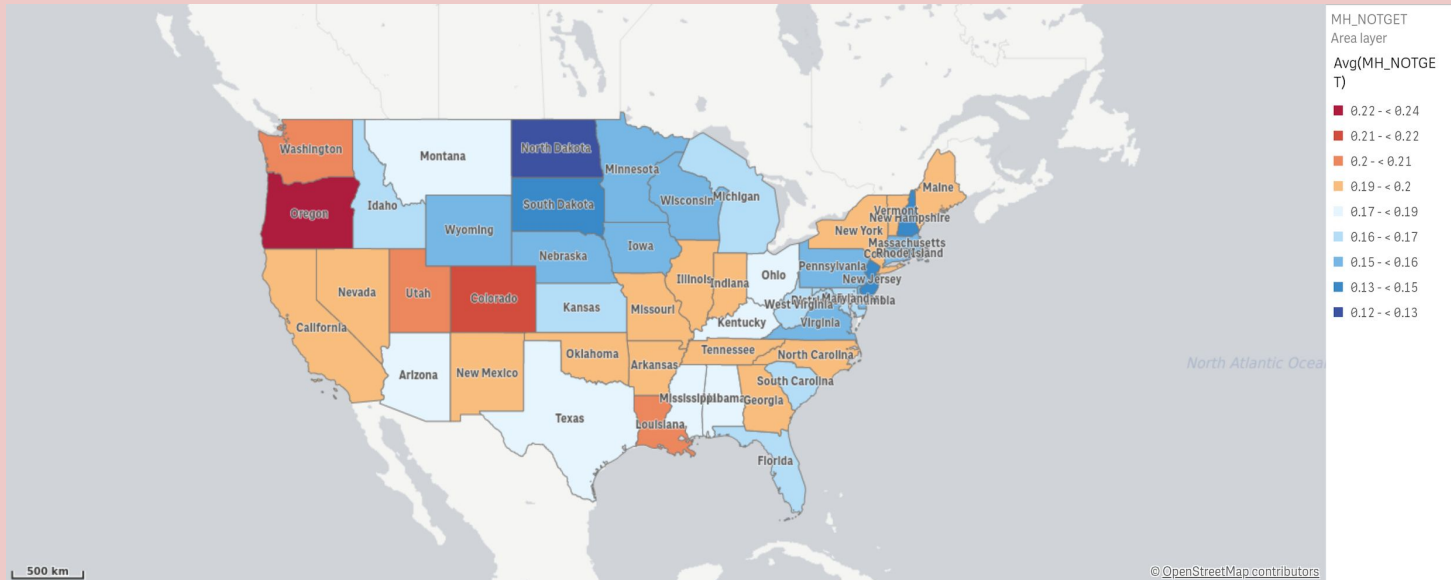
3

AGE :
How old are you?

FEATURE
IMPORTANCE

Distribution of avoidance behaviour

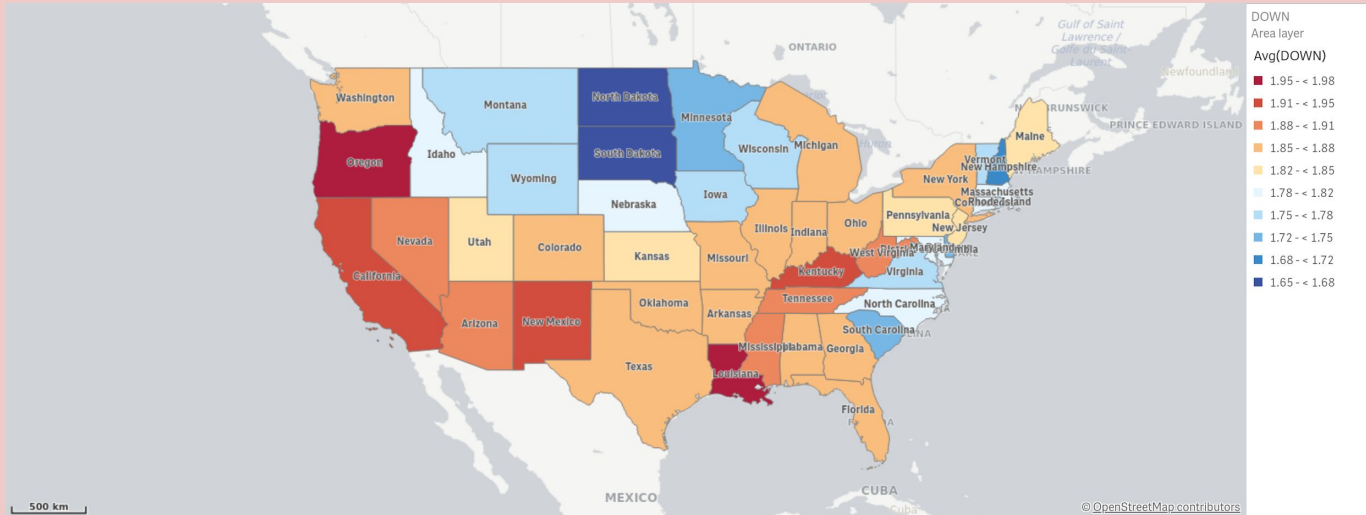
- High percentages: Oregon, Washington
- Low percentages: North and South Dakota
- Oregon and Colorado ranked **48th** and **47th** respectively in mental health



FINDINGS

1) Constantly feeling down

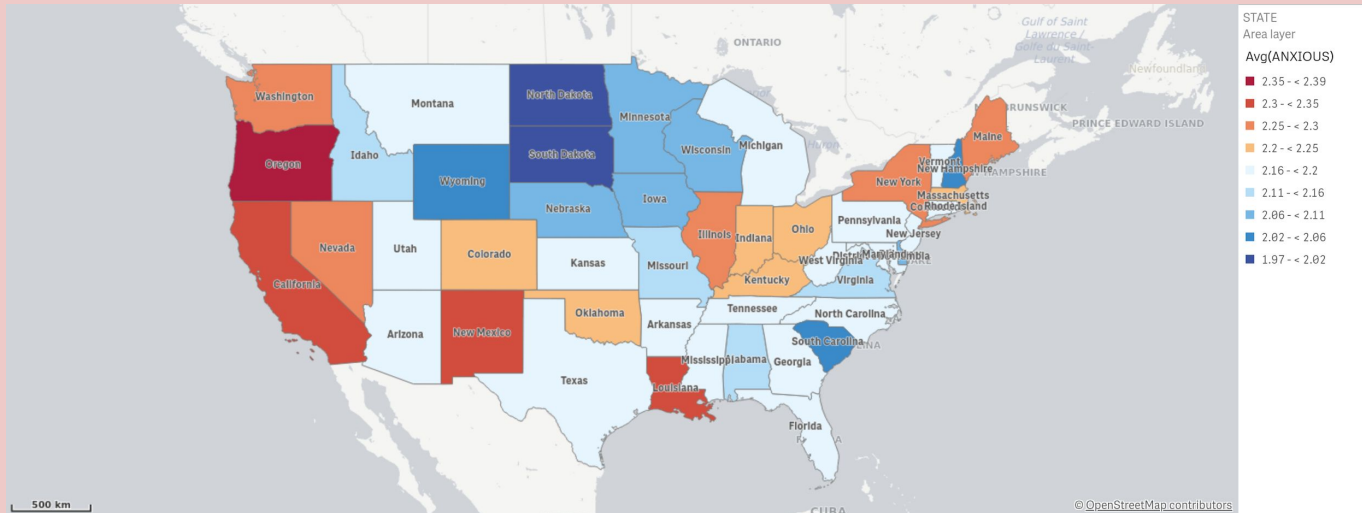
- Strong correlation between **high** frequency of feeling sad/hopeless and development of avoidance behaviours
- A **common symptom** of depression
- High anxiety levels: Oregon, Louisiana
- Low anxiety levels: North and South Dakota



FINDINGS

2) Constantly feeling anxious

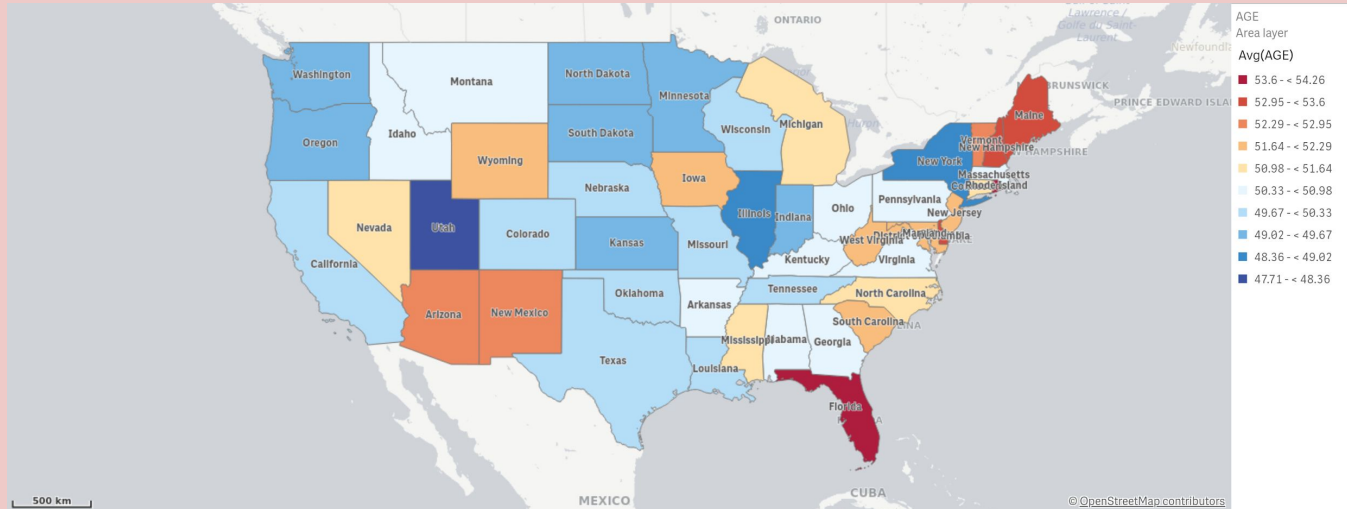
- Strong correlation between **high** frequency of feeling anxious and development of avoidance behaviour
- A **common symptom** of anxiety disorders
- High anxiety levels: Oregon, Washington
- Low anxiety levels: North and South Dakota



FINDINGS

3) Younger population

- Correlation between a younger population and development of avoidance behaviour
- Average age of respondents that do not exhibit such behaviours: **52.0**
- Average age of respondents that do exhibit such behaviours: **44.2**



FINDINGS

	Logistic Regression	XgBoost	Random Forest	k-NN	Neural Nets	Extra Trees
CV Recall	0.776	0.921	0.824	0.733	0.702	0.840
Train Recall	0.777	0.999	0.861	0.744	0.843	0.870
Test Recall	0.799	0.940	0.839	0.750	0.836	0.856
Train ROC-AUC	0.775	0.881	0.807	0.769	0.799	0.797
Test ROC-AUC	0.787	0.743	0.771	0.771	0.790	0.770

MODEL
EVALUATION

Extra Trees Classifier

CONFUSION MATRIX

	PREDICT NEGATIVE	PREDICT POSITIVE
ACTUAL NEGATIVE	13816	6402
ACTUAL POSITIVE	647	3711

MODEL
PERFORMANCE

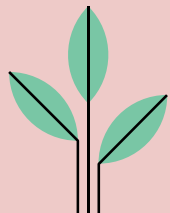
Re-evaluating false positives

Criteria for False positives?
DOWN ≥ 3 , ANXIOUS ≥ 3

	False positives	False positives?
Total	6402	2117

	Age of actual positives	Age of false positives?
Average	44.2	46.2





1

Bias in responses:
Response bias and self-reported assessment of mental health status is highly subjective.

2

Imbalanced classes:
Undersampling was done randomly to reduce the number of majority class which would disregard potentially important features

3

Unrepresentative data:
Insufficient data on minority class and thus model could be overfitted with this particular class. Groups of people such as those without internet access/people who are institutionalized are excluded

LIMITATIONS



Implement model on a smaller scale and as reference

Critical features identified (DOWN, ANXIOUS, age) would be the deciding factors on where to implement models. Models viable as references, not indicative of actual mental health disorders



Implement model in dire state - Oregon

Propose models to Oregon Health Authority are Oregon marked the checkboxes for high ANXIOUS, high DOWN and a younger population



Implement model in states that show similar trend - Utah, Illinois

Medium to high levels of DOWN and ANXIOUS with a growing population

- Utah has a resident: behavioural professionals ratio below national average
- Illinois has per capita expenditure on health services below that of national average

CONCLUSION



THANK YOU

ANY QUESTIONS?

