Predicting Mental Health Treatment at US Companies

Supervised Machine Learning Report

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1. INTRODUCTION

OBJECTIVE:

Analyze mental health survey responses to find predictors for whether American employees will seek mental health treatment

DATA (source):

- Global 2014 – 2016 mental health survey – majority in US
  - **1259** total responses (global)
  - **751** USA responses (~60% of total)
  - **27** features
- Explores employee & employer attitudes towards mental health in workplace
  - Employee demographic info; mental health history & treatment
  - Employer-offered mental health benefits & care options

2. DATASET

FEATURES:

- **Employee Info**
  - Demographics – Age, gender, location, type of employment
  - Write-in comments
  - Mental illness
    - Family history
    - Currently seeking treatment **(TARGET)**

- **Employer Attitudes & Work Environment Offerings**
  - Size & type of company
  - Availability of mental health benefits & care options
  - Value & prioritization of mental health in workplace

3. DATA CLEANING

FEATURES TO CLEAN:

- **Age**
  - Invalid ages – below 0 & over 120
    - 5 rows dropped
  - Normalize using min-max scale

- **Gender**
  - Employees' write-in responses
  - Clean & Categorize
    - 'Male', 'Female', & 'Other' (i.e. Queer / Non-Binary) → 'Male' & 'Female'
    - 13 rows of 'Other' dropped

FEATURES WITH MISSING VALUES:

- **state**
  - 515 → 11 rows, after focusing on just US employees
  - All 11 rows dropped

- **self_employed**
  - 18 NaN rows dropped

- **work_interfere**
  - 264 rows
  - Impute all NaNs to most common category (‘Sometimes’)

- **comments**
  - 1095 rows (significant percentage)
  - Save for later feature engineering

4. FEATURE ENGINEERING

LOCATION & TIME FEATURES

- **Country → Continent**
  - Later removed to focus on US
- **US Regions**
  - North, South, East, West, Midwest
- **Years**
  - 2014, 2015, 2016
- **Seasons**
  - Spring, Summer, Fall, Winter

COMPARISON FEATURES

- **mental_ vs. physical_consequence**
  - More worried about workplace consequences due to ____ health
- **mental_ vs. physical_interview**
  - More likely to mention ____ health in interview

OTHER FEATURES

- **has_comment**
  - 0 (False) or 1 (True); majority 0
- **comment_len**
  - Char lengths of comments ; majority = 0

5. HANDLE SKEWED DATA

SKEWED DATA

- Need 1:1 ratio for people seeking vs. not seeking mental health treatment
- **NOTE** – data not so skewed that skipping over-sampling would have given significantly worse scores

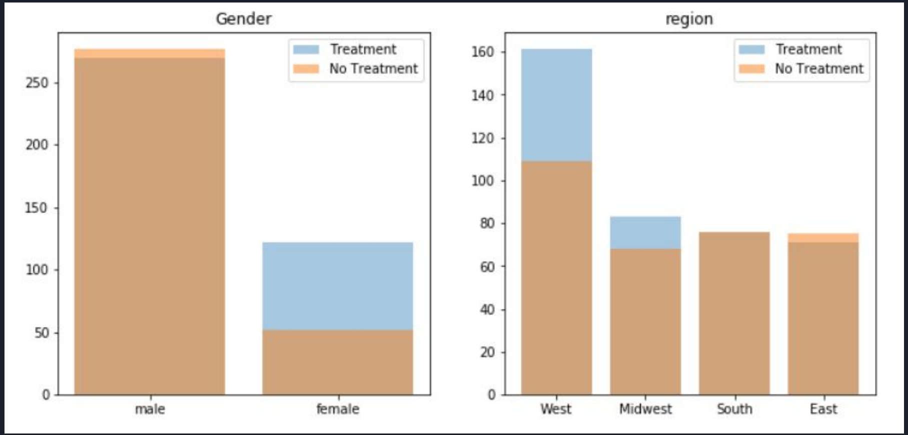
OVER-SAMPLING VIA SMOTE

- Split into train & test datasets
- Over-sample the train dataset to achieve 1:1 ratio
    - Over-sampled train → Over-sampled X (train & test); Over-sampled Y (train & test)

6. EXPLORE & ANALYZE

NARROW FOCUS:

- Just US employees
- Takes care of some missing rows (e.g. state)
- 2 groups to compare
  - Seeking vs. Not Seeking Treatment

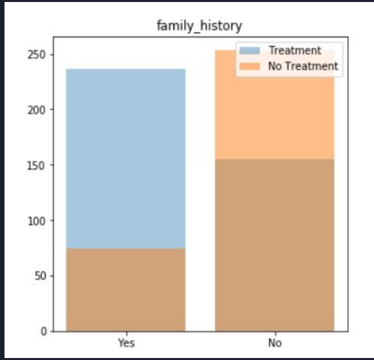


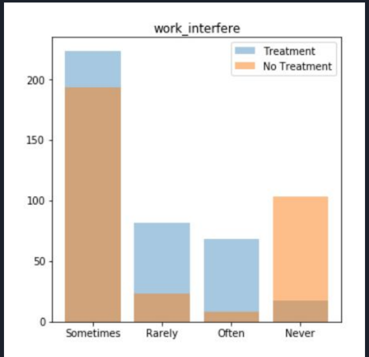
EDA FINDINGS:

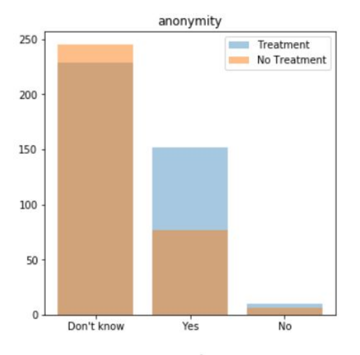
- Gender
  - More women seeking treatment
- Region
  - More employees on West coast seeking treatment

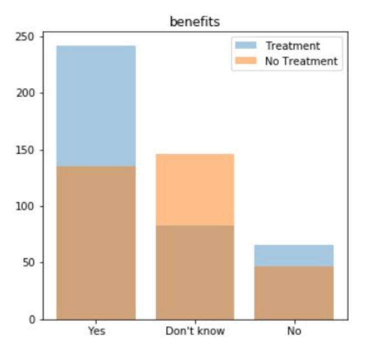
EDA FINDINGS, cont’d:

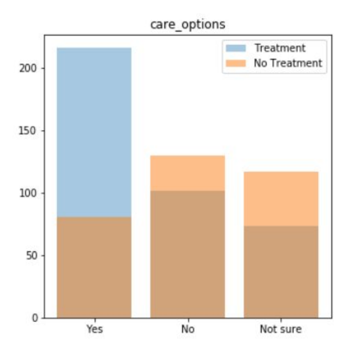
- **Employees seeking treatment more often have:**
  - Family history of mental illness
  - Mental health issues frequently affecting their work
  - Anonymous access to mental health help
  - Work-provided mental health benefits & care options











7. MODEL SELECTION

TARGET:

Predict whether or not an employee is seeking mental health treatment

STRATEGY:

- Create & evaluate several classifier models
  - Fit on over-sampled train
  - **TRAIN SCORE**: Score on over-sampled test
  - **TEST SCORE**: Score on test dataset
  - **WHOLE SCORE**: Score on whole dataset

PREPARATION:

- **Normalization** of Continuous Variables
  - Age, comment_lens
- **Dummies** for Categorical Variables
  - Gender, self_employed, family_history, region, etc.

MODELS TO BUILD:

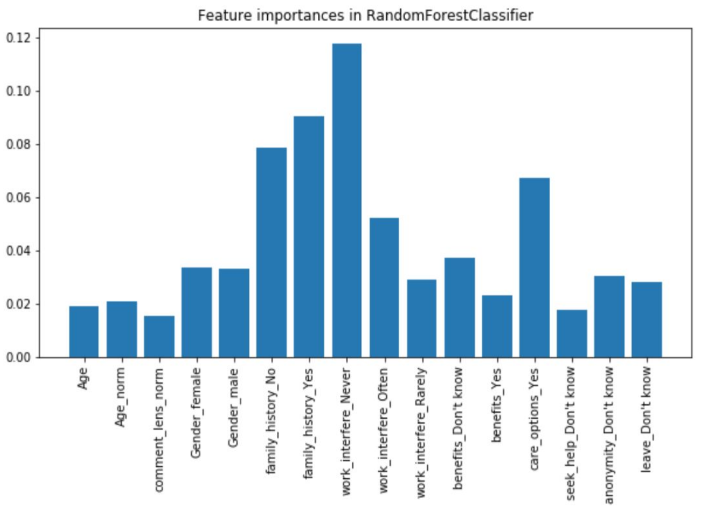
- LASSO Logistic Regression
- Random Forest Classifier
- Naive Bayes Classifier
- Gradient Boosting Classifier
- Support Vector Classifier

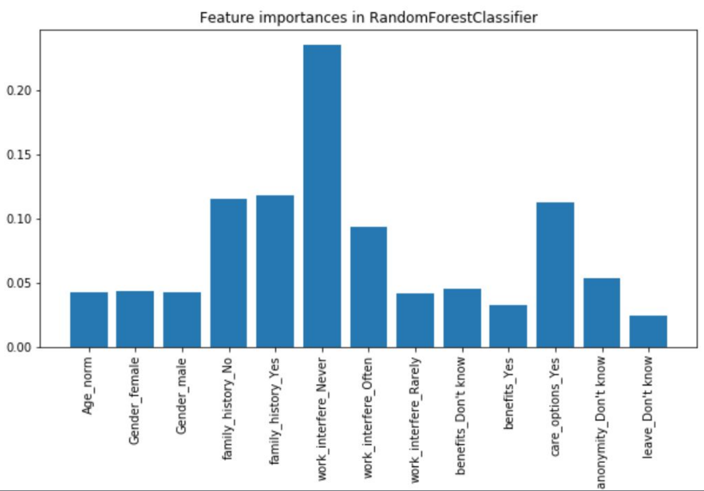
8. MODEL EVALUATION

	LASSO Logistic Regression	Random Forest Classifier	Naive Bayes Classifier	Gradient Boosting Classifier	Support Vector Classifier
R^2 **(train, test, whole)**	74.8% 80.8% 78.2%	72.3% 79.0% 78.0%	71.4% 75.3% 72.7%	70.6% 90.3% 82.3%	74.8% 91.9% 80.0%
Precision & Recall **(train, test, whole)**	85.0%, 80.6% 86.0%, 77.7% 82.1%, 76.5%	85.0%, 80.6% 82.4%, 78.2% 80.9%, 78.0%	76.9%, 76.9% 77.3%, 77.7% 75.7%, 73.4%	100.0%, 100.0% 92.2%, 89.9% 84.7%, 82.4%	100.0%, 100.0% 95.2%, 89.9% 84.8%, 76.7%
Type I & II Errors **(train, test, whole)**	6.9%, 9.5% 6.9%, 12.2% 9.0%, 12.8%	6.9%, 9.5% 9.2%, 11.9% 10.0%, 12.0%	11.3%. 11.3% 12.5%, 12.2% 12.8%, 14.5%	0.0%, 0.0% 4.2%, 5.6% 8.1%, 9.6%	0.0%, 0.0% 2.5%, 5.6% 7.5%, 12.7%

STRATEGY #1:
USE PREVIOUS IMPORTANT FEATURES:

- Get most important features from previously fitted Random Forest Classifier
- Feed these features to most successful models (RFC, GBM, & SVC)
- Results
  - **RFC** – slightly lower R^2 & precision / recall rates; slightly higher errors (higher feature importances)
  - **GBM & SVC** – lower & more erratic R^2 & precision / recall rates





REGULAR MODEL

```
***TRAIN***
R² for train: 0.8103448275862069
predicted      0    1  All
actual
0            109   24  133
1             24  113  137
All          133  137  270

Type I errors: 8.89%
Type II errors: 8.89%

Precision: 82.48%
Recall: 82.48%

***TEST***
R² for test: 0.8164383561643835
predicted      0    1  All
actual
0            135   37  172
1             30  163  193
All          165  200  365

Type I errors: 10.14%
Type II errors: 8.22%

Precision: 81.5%
Recall: 84.46%

***WHOLE***
R² for whole: 0.7780821917808219
predicted      0    1  All
actual
0            252   82  334
1             80  316  396
All          332  398  730

Type I errors: 11.23%
Type II errors: 10.96%

Precision: 79.4%
Recall: 79.8%
```

MODEL WITH PREVIOUS IMPORTANT FEATURES

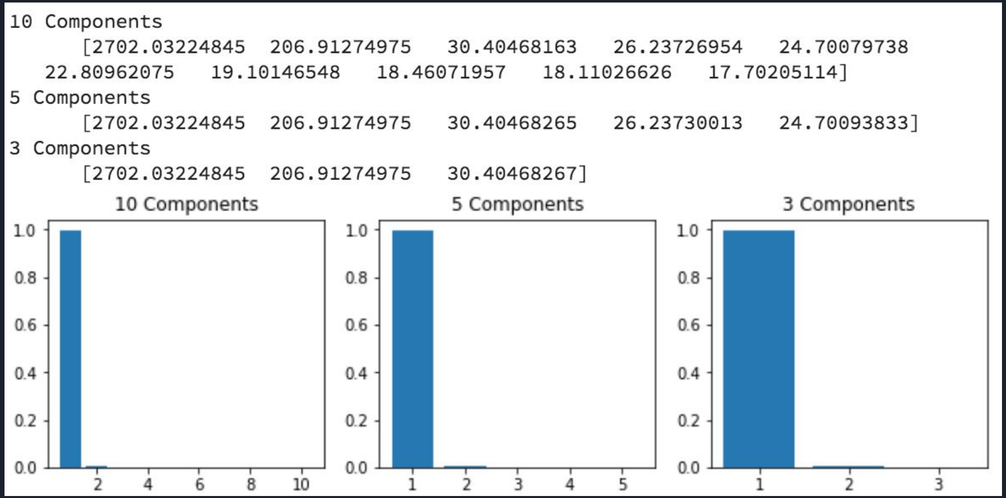
```
***TRAIN***
R² for train: 0.8017241379310345
predicted      0    1  All
actual
0            107   26  133
1             29  108  137
All          136  134  270

Type I errors: 9.63%
Type II errors: 10.74%

Precision: 80.6%
Recall: 78.83%

***TEST***
R² for test: 0.7917808219178082
predicted      0    1  All
actual
0            132   40  172
1             36  157  193
All          168  197  365

Type I errors: 10.96%
Type II errors: 9.86%

Precision: 79.7%
Recall: 81.35%

***WHOLE***
R² for whole: 0.7589041095890411
predicted      0    1  All
actual
0            247   87  334
1             89  307  396
All          336  394  730

Type I errors: 11.92%
Type II errors: 12.19%

Precision: 77.92%
Recall: 77.53%
```

COMPARISON CONCLUSION:

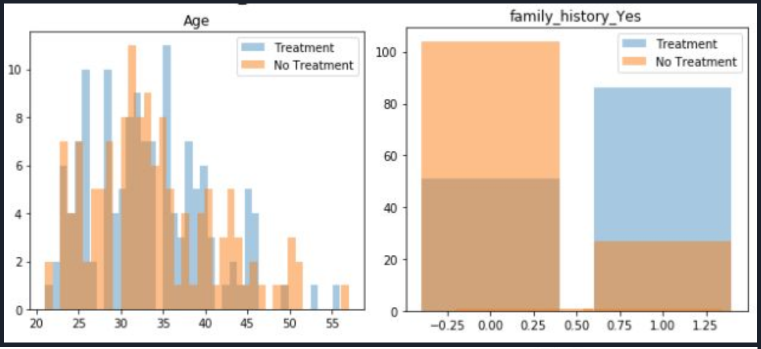
- Will choose original model over new model with previously selected important features
  - Slightly lower R^2 (insignificant difference)
  - Slightly lower precision & recall rates (insignificant difference)
  - Errors all get slightly higher

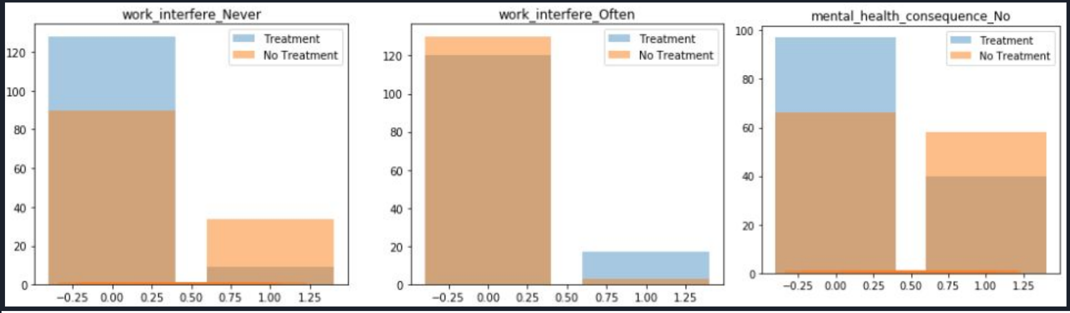
STRATEGY #2:
USE PCA TO REDUCE FEATURES:

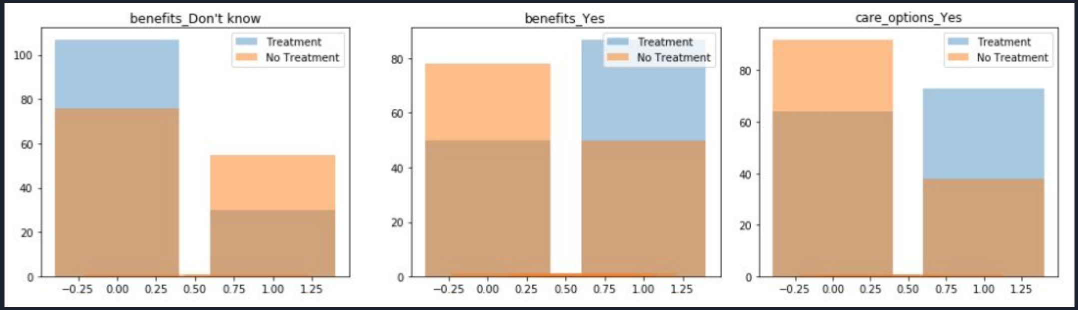
- Reduced to 3 components
  - Only 1 important component
- Feed PCA features to most successful models (RFC, GBM, & SVC)
- **All models** – much lower & more erratic R^2, precision & recall rates (sign of overfitting)
- PCA won't work because most variables are categorical



9. FINDINGS







<u>Employees most likely to seek mental health treatment:</u>

- Women in late 20s to mid-30s
- Family history of mental health
- Mental health interfering with work
- Have & are aware of mental health benefits & care options at workplace
- Want to avoid mental health discussions with employer
    a. Most interesting discovery
    b. Avoid cause-effect conclusions

10. NEXT STEPS

Takeaways for Employers & Employees:

- More conversations ("openness") with coworkers & bosses may not be as helpful or appealing to employees seeking treatment as simple availability & awareness of mental health resources
- Understanding how untreated mental health can interfere with work and impact the company may incentivize employers to invest in their teams' mental health

Further Study:

- Incomplete data picture
  - Specific mental illness employees suffer from
  - Frequency, severity, & kinds of treatment being administered (talk therapy, group therapy, medical procedures, medication, etc.)

THANK YOU

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