PRUDENT CHOICE

Build a model to help Prudential come up with a response to life insurance applicants

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DATA SOURCES

Kaggle (https://www.kaggle.com/c/prudential-life-insurance-assessment)

Prudential Life Insurance company

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PROJECT GOAL

Analyze features collected from life insurance applicants provided by Prudential and build a model to predict the company's likely response.

Motivation for the problem:

Prudential wants to make it quicker and less labor intensive for customers to get a quote while maintaining privacy.

Status quo inefficient: takes the company a long time to come up with a decision, losing customers in the process.

If we come up with a model that accurately predicts the decisions the company comes up, the model can be incorporated to swiftly make decisions.

SIMILAR CASES

- Providing loans to individuals/businesses.
- Solution: models that analyze customer features and provide a credit score to help banks and financial institutions decide whether to provide a loan to an applicant.

ANALYSIS APPROACH

1. Data preparation
   - Overview of features and outcome
   - Feature engineering
   - Dealing with missing values
   - Normalization

2. Exploratory data analysis

3. Training, testing & cross-validation
   - Fit logistic regression, KNN, Random Forest and Gradient Boosting Classifier on a small sample of the dataset
   - K-fold cross-validation for multiple values of K
   - Learning curve to assess adequacy of data
   - Model performance evaluation (accuracy of prediction)
   - Feature selection
   - Test on out of sample test data set — get score from Kaggle

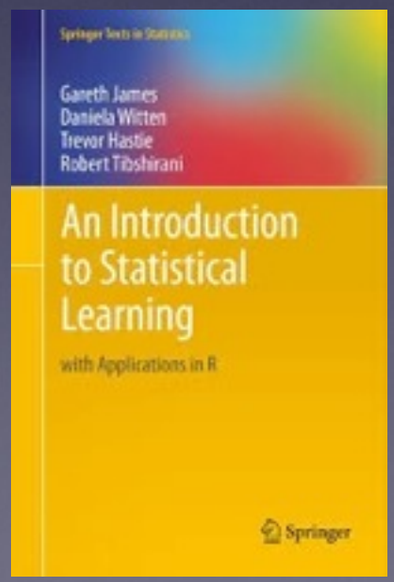
OVERVIEW OF DATA

- There are ~50,000 rows and 127 columns: 126 features and 1 outcome column. Outcome column is called “Response” and is nominal with 8 values (1,2,3,4,5,6,7,8).

- Most features are de-identified; we have a vague idea about what they might represent: “Product_Info”, “Employment_Info”, “Medical_keyword”.

- All but one feature columns are numeric.

RESOURCES USED FOR ANALYSIS



FEATURE ENGINEERING

- Obtained dummy variables for columns for which unique values were less than 0.5% of the total values.

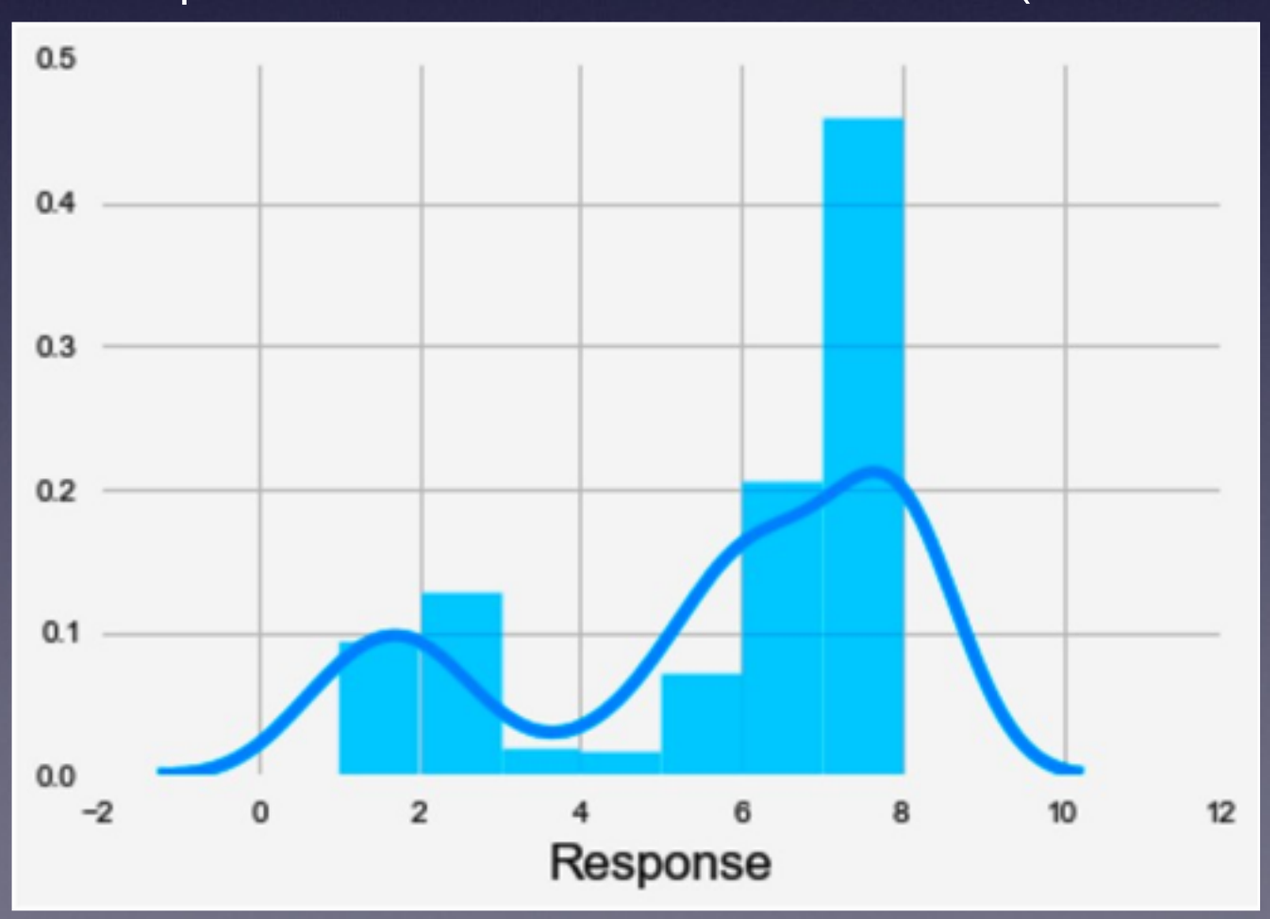
IMPUTING MISSING VALUES

- Imputed missing values with the median value of the columns.

FEATURE & RESPONSE DISTRIBUTIONS

- Distribution of the variables are normalized (according to Kaggle). If not, I would have looked at histograms, determined mean and stdev and scaled accordingly.

- Response column distribution (randomly sampled data: 500 rows)

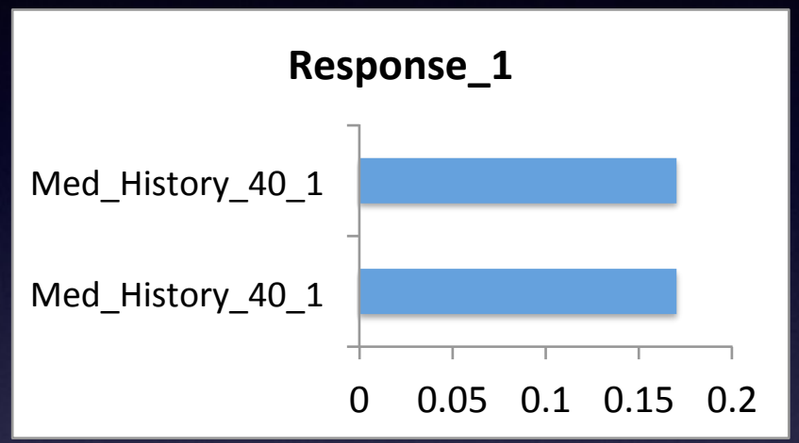


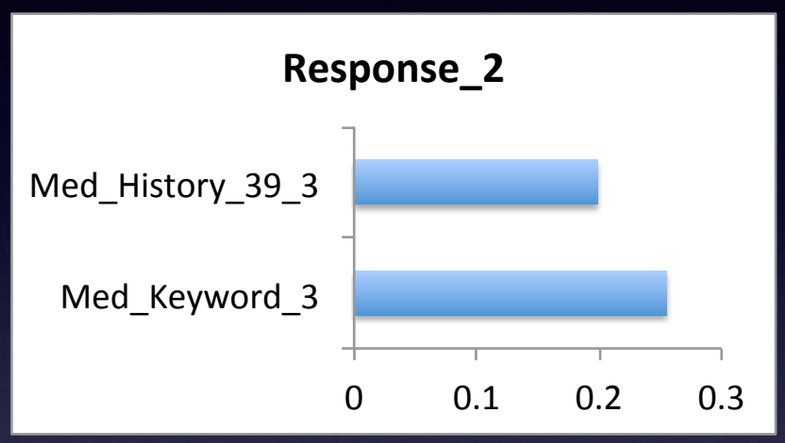
To consider:

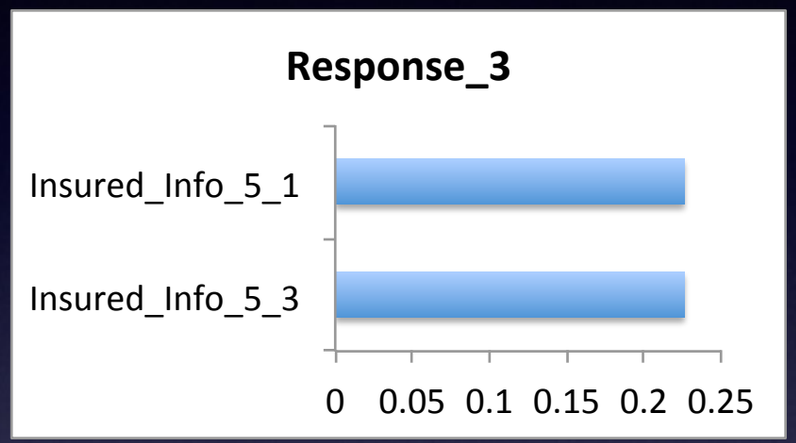
- SMOTE or upsampling #3,4
- Undersampling #7,8

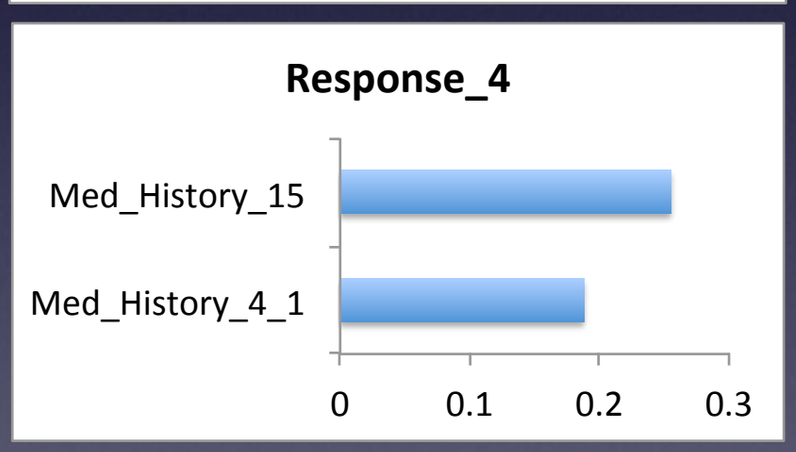
Exploratory data analysis -I

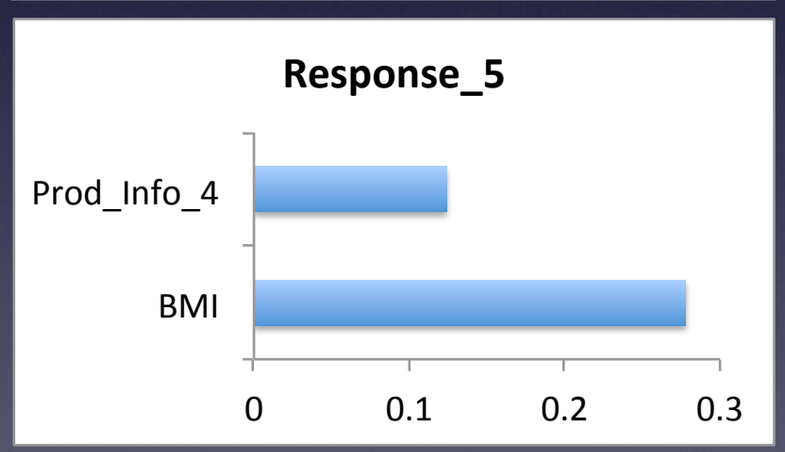
2) Most positively and negatively correlated feature for each response

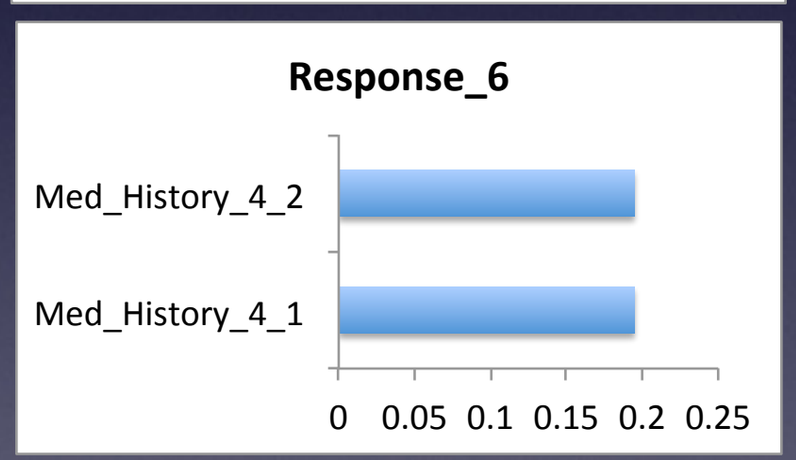


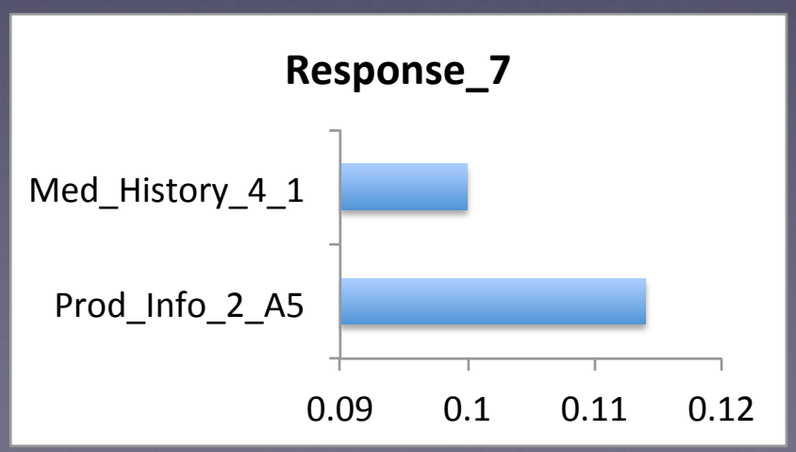


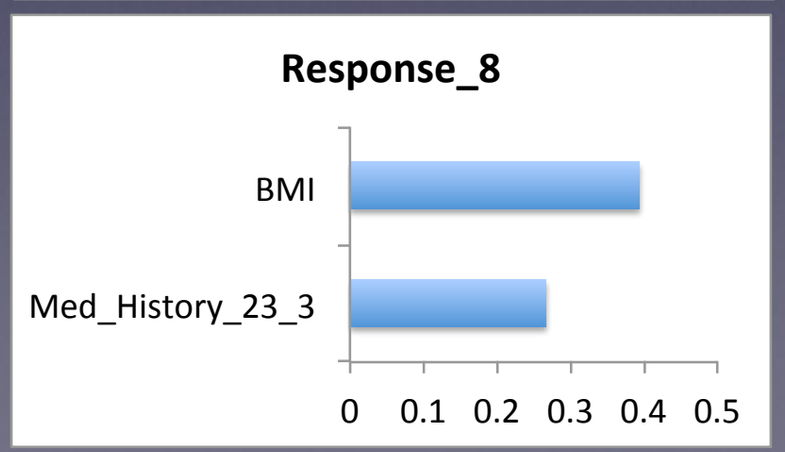






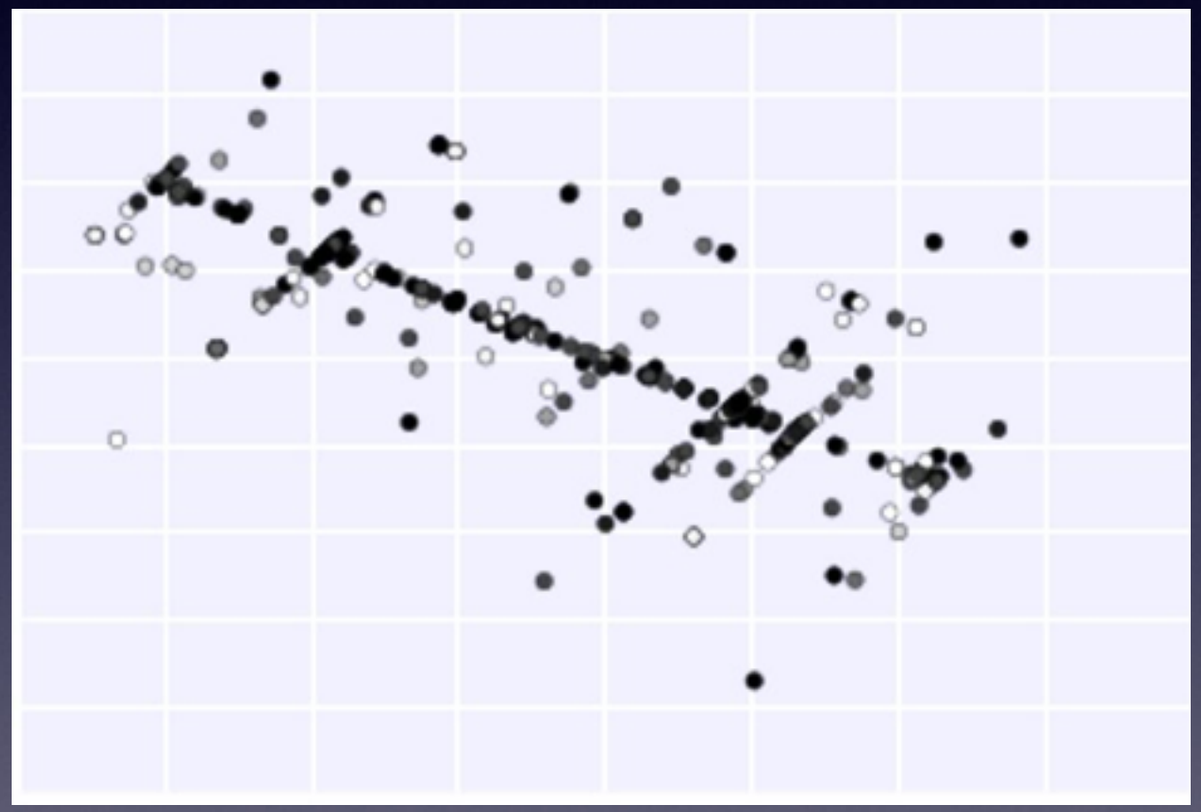






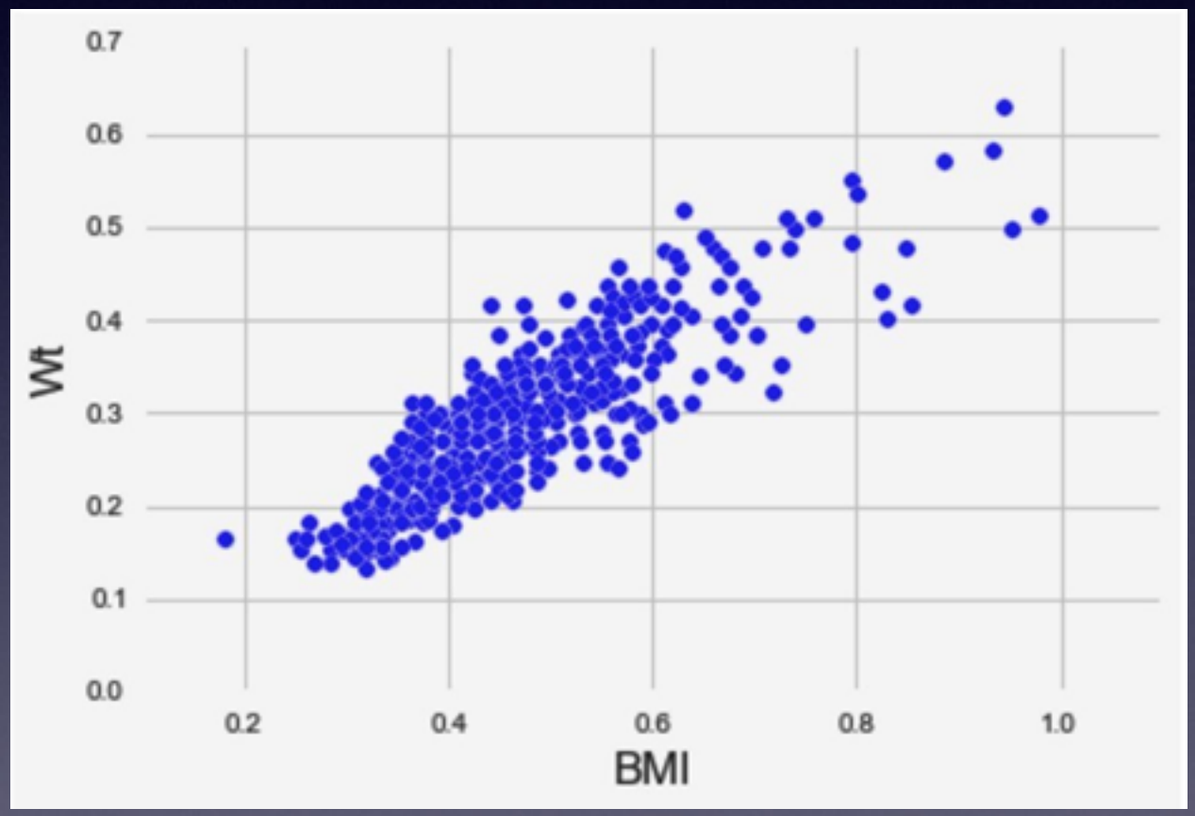
Exploratory data analysis -I

1) 2D projection of feature space using MDS, colored by *Response* shows that responses aren't clearly separable



Exploratory data analysis -II

BMI is positively correlated with Weight (subset of data)



Training a model - First Pass

- Using all features on a small sample of the data, I fitted the following models:
    - Random Forest Classifier
    - K-Nearest Neighbor Classifier
    - Logistic Regression
    - Gradient Boosting Classifier

- K-fold cross-validation score (Insert graph).
- Learning curve shows that we have enough data.

Measuring Model Performance

- My choice of model performance metric was “accuracy” (% of times the model guessed correctly).
    - Logistic Regression: 33% accuracy
    - K-Nearest Neighbor Classifier: 21%
    - Naive Bayes: 19%
    - Gradient Boosting Classifier: 46.6% accuracy
- For this competition, Kaggle evaluates submissions on a different metric: weighted kappa. Though there are ways to incorporate custom scoring metrics, I left this out for a later stage since I wanted to focus on getting my model predictions to be as accurate as possible.

Next Steps

- Make Response column more even : SMOTE/undersample
- Run the models on the entire dataset on Amazon’s EC2 cloud server.