Crunchbase Funding Prediction Model

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Objective

Predict whether or not a company will get funded in the following year based on data at a given time.

Problem

There Are A Lot Of Startups Out There.

Can We Predict The Ones Worth Funding?

About The Data

Following Datasets Provided by Crunchbase (Up to 2015):

	Shape	Numeric Data	Text Data	Datetimes
Company Data	(51146, 14)	2	9	3
Investment Rounds Data	(212810, 18)	1	16	1
Organization Data	(606064, 16)	0	16	0
People Data	(605630, 15)	0	15	0
Acquisition Data	(18968, 18)	1	15	2
IPO Data	(1259, 13)	2	8	3

Approach

1. Data Cleaning & Wrangling

2. Exploratory Data Analysis

3. Random Forest Classifier

4. Model Evaluation

5. Analyze Results

Data Cleaning & Wrangling

Goal For Final Dataset:

- **Features and Target Are All Numeric Values**
- **Each Row Represents One Fiscal Quarter Of A Company**
- **Features Summarize All Important Data From Original Datasets**
- **Target Shows Whether Company Is Funded In Coming Year**

Processed Data

Final Dataset

- **About 1,600,000 Rows**
- **111 Numeric Features**
- **2 Text Features (HashingVectorizer)**

Features Categories

- **Company Features**
- **Investment Round Features**
- **Investor Features**
- **Macro Features**

Exploratory Data Analysis (EDA)

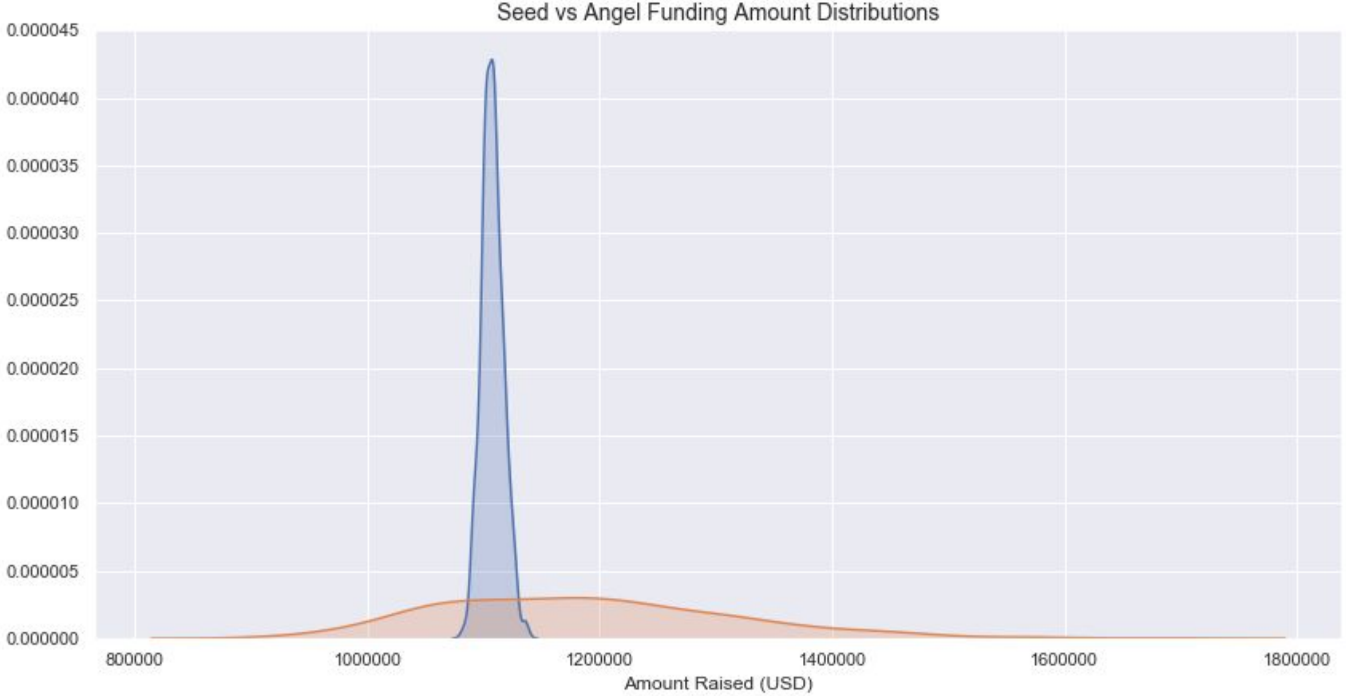
1. Investment Analysis

2. Investor Analysis

3. Category Analysis

EDA: Investment Analysis

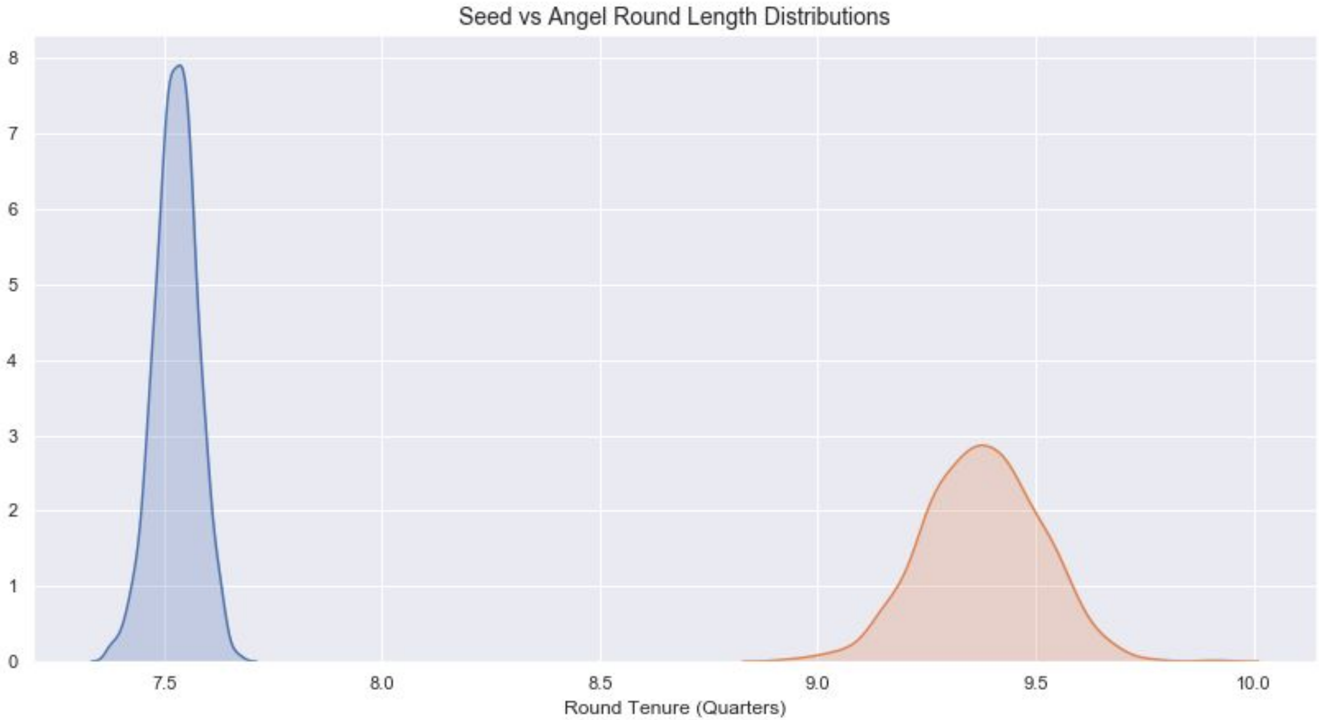
Analyzing Round Amounts (Other Rounds in Notebook)



Observation: *Seed rounds (blue) have less variance but tend to have lower funding amounts.*

EDA: Investment Analysis

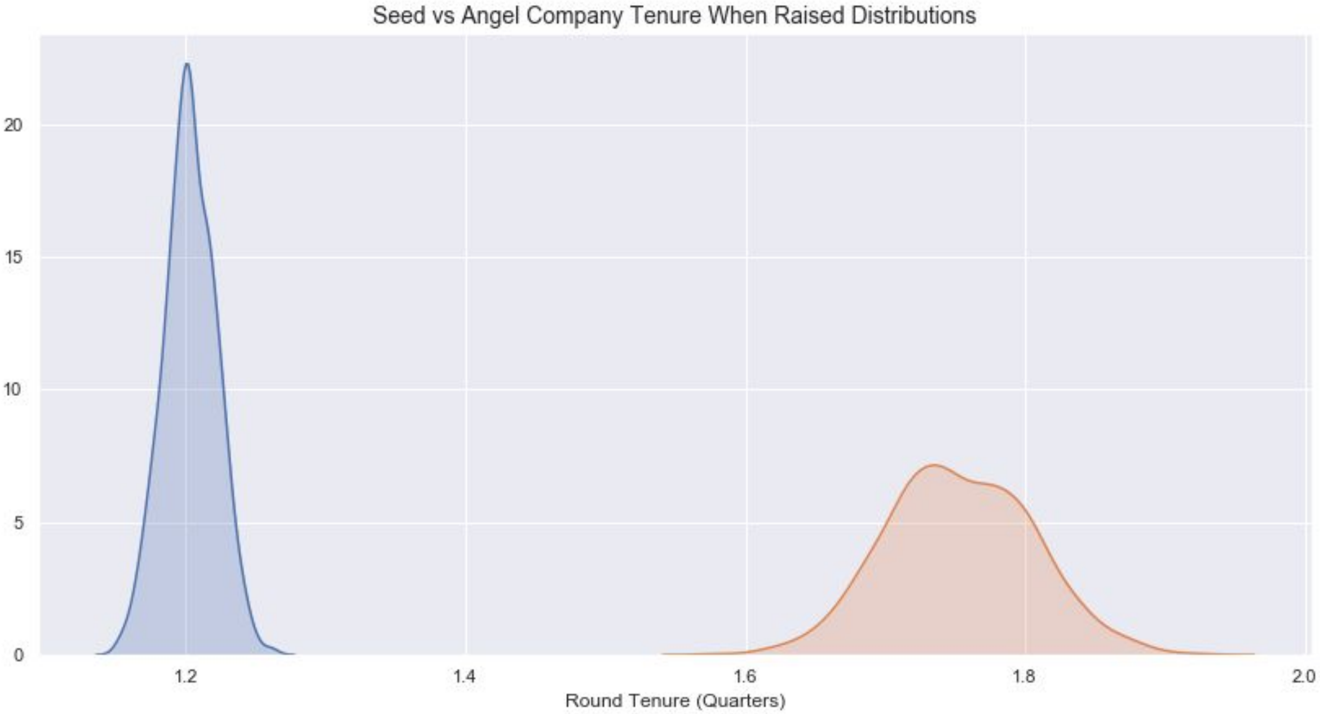
Analyzing Round Lengths (Other Rounds In Notebook)



Observation: *Seed Funded Rounds (blue) are usually shorter than Angel Rounds.*

EDA: Investment Analysis

Analyzing Company Tenure At Funding (Other Rounds In Notebook)



Observation: *Seed Rounds (blue) are usually raised faster than Angel Rounds.*

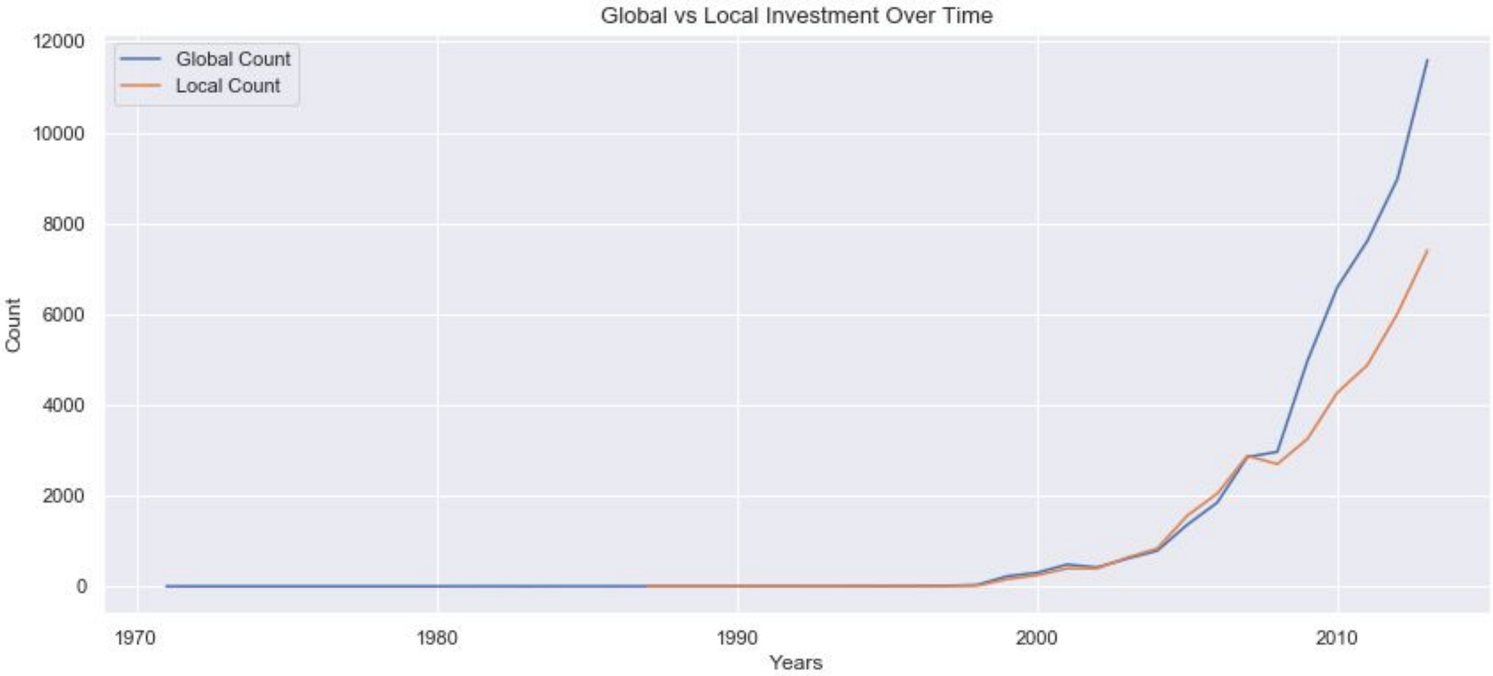
EDA: Investment Analysis

Key Observations (Full Analysis In Notebook)

- **Funding Amount by Angels Have A Higher Variance Than Seeds.**
- **Later Rounds** Typically Have **Higher Variance** in Amount & Tenure.
- **Round Length For Venture Rounds** Tends to be **between 10 - 15 Quarters.**
- **Equity Funding is Greater Than Debt Before IPOs but Less After.**

EDA: Investor Analysis

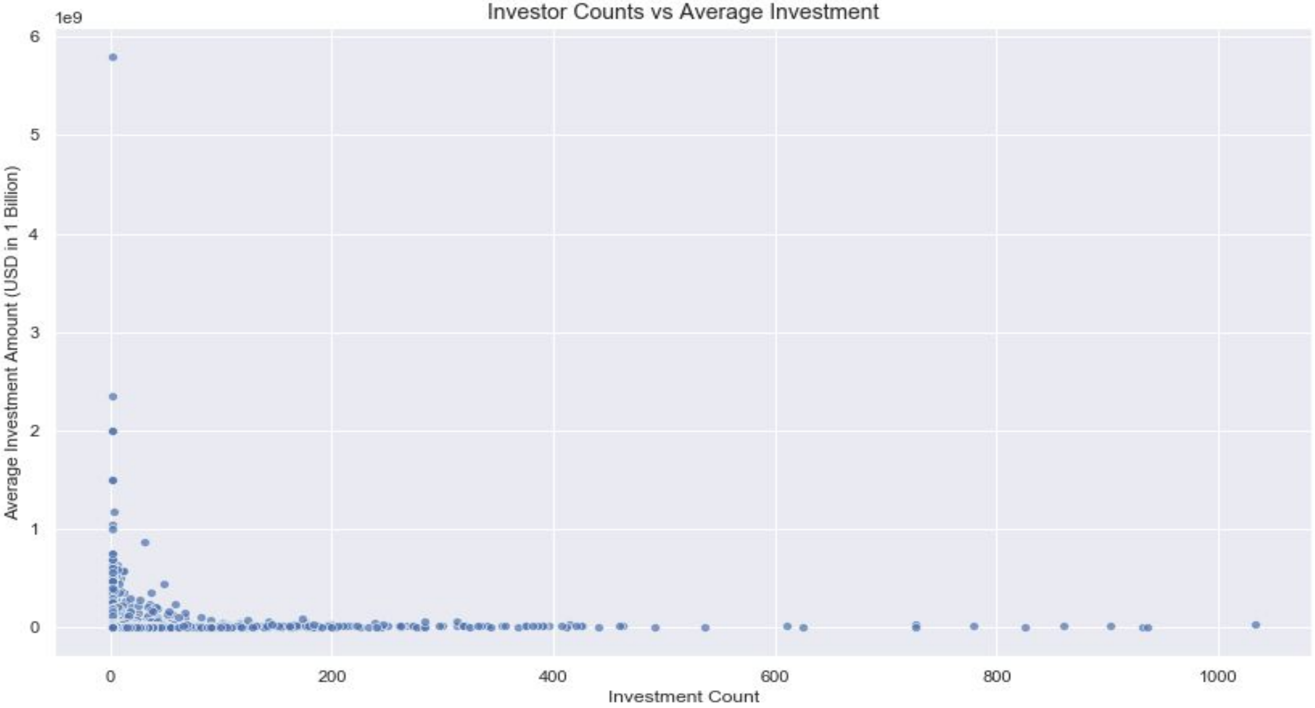
Analyzing Globalization of Investing (Full Analysis In Notebook)



Observation: *Since 2007 more investments are being made abroad than locally.*

EDA: Investor Analysis

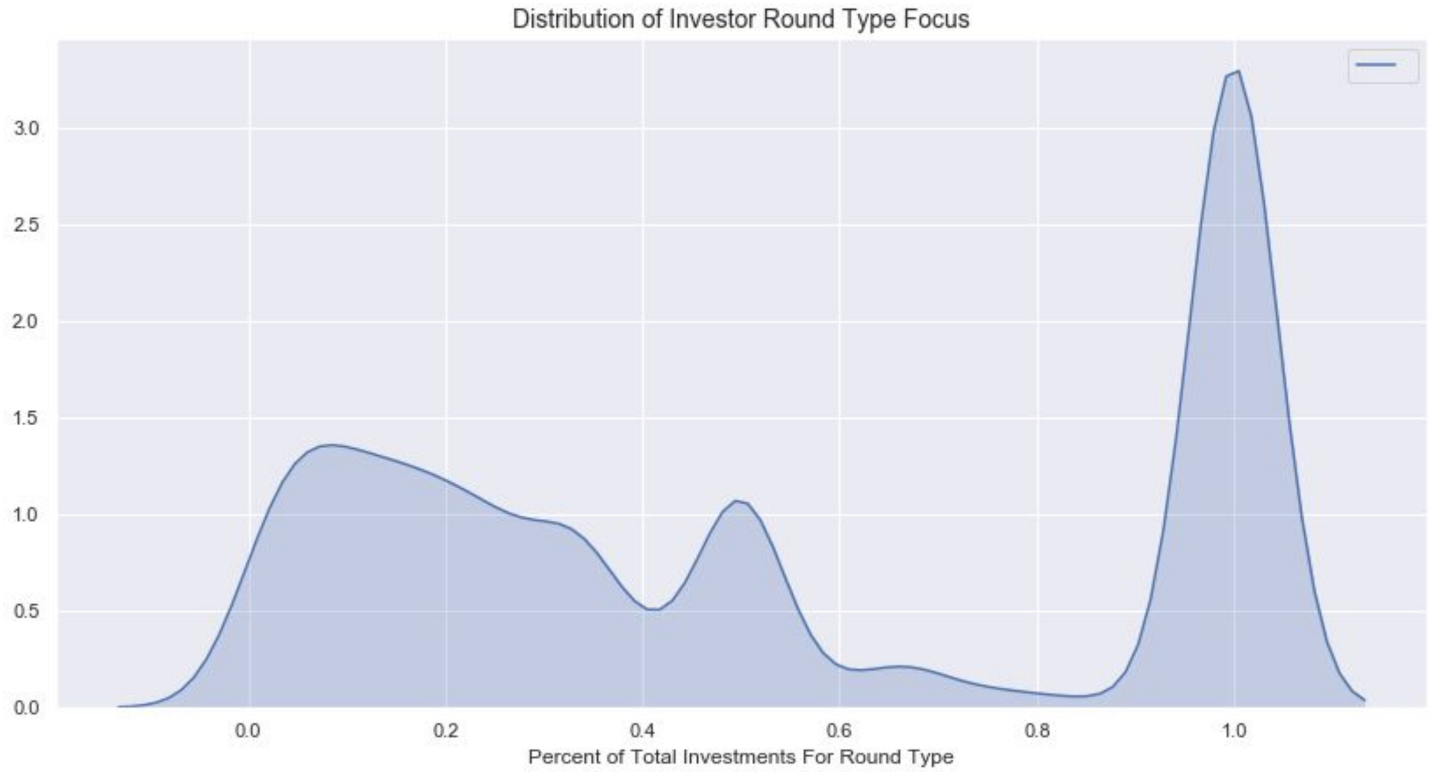
Analyzing Differences In Investor Strategy (Full Analysis In Notebook)



Observation: *Initial visualization seems to show that investors may focus on many small investments or few large investments but turns out this is* ***not statistically significant****.*

EDA: Investor Analysis

Do Investors Focus On Specific Round Types? (Full Analysis in Notebook)



EDA: Investor Analysis

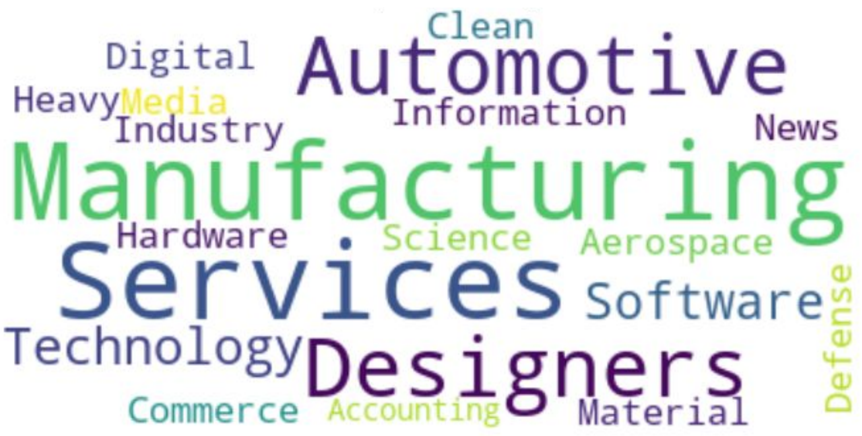
Key Observations

- **There Are More Gaps in Data of Global Investors**
- **Difference in Invested Amount** of Global and Local Investors **is NOT statistically significant**
- **Investors Do NOT Focus** On Just **Many Small** or **Few Large Investments But Have Varying Strategies Overall.**
- **Most Investors Focus On More than One Round Type.**
- **Seed Investors** Tend to **Focus on Seed Funding**.

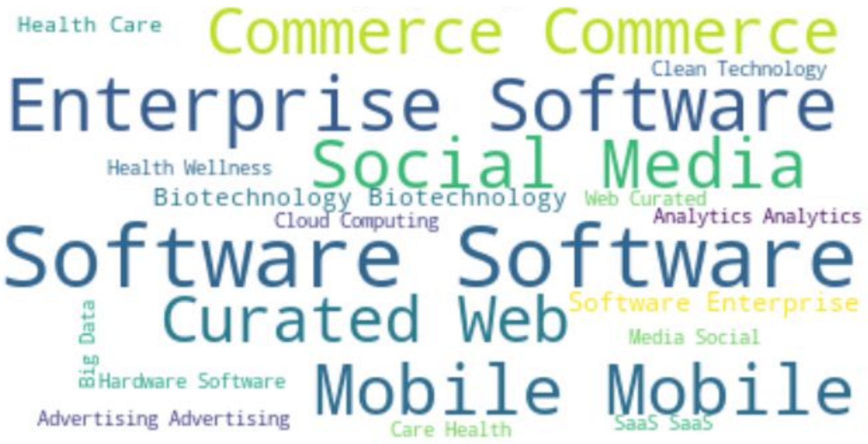
EDA: Category Analysis

Analyzing Funded Categories Over Time

Top Categories in the 1980s



Top Categories in the 2010s



EDA: Category Analysis

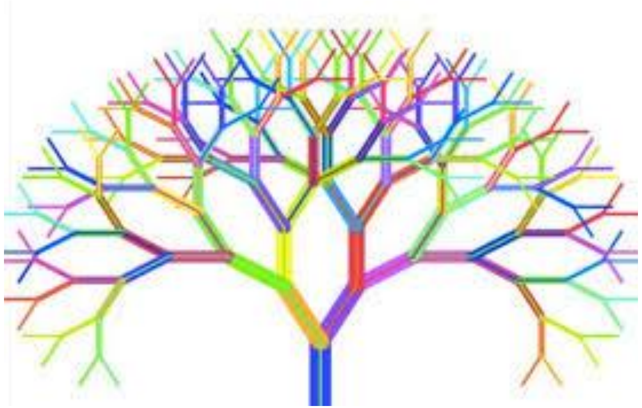
Analyzing Funded Categories Over Time (Full Analysis In Notebook)

- **1980s:** Manufacturing, Services, Designers, Automotive, Technology
- **1990s:** Software, Technology, Curated Web, Service, Internet
- **2000s:** Software, BioTech, Enterprise Software, Mobile, Curated Web
- **2010s:** Software, Enterprise Software, Mobile, Curated Web, Commerce

Choosing The Model

Why Random Forest Classifier?

- Flexible
- Prevents Overfitting
- High Feature & Sample Count
- No Scaling Required



Training The Model

Input Data After HashingVectorizer

- **111** Numeric Features
- **3000** HashingVectorizer Features

Pipeline

- **FeatureUnion**
  - **Imputer**
  - **HashingVectorizer**
  - **SelectKBest**
- **RandomForestClassifier**

Hyperparameter Tuning

***Default Parameters* Yielded Best Results!**

Model Evaluation

Accuracy: 0.94

Avg CV Score: 0.89

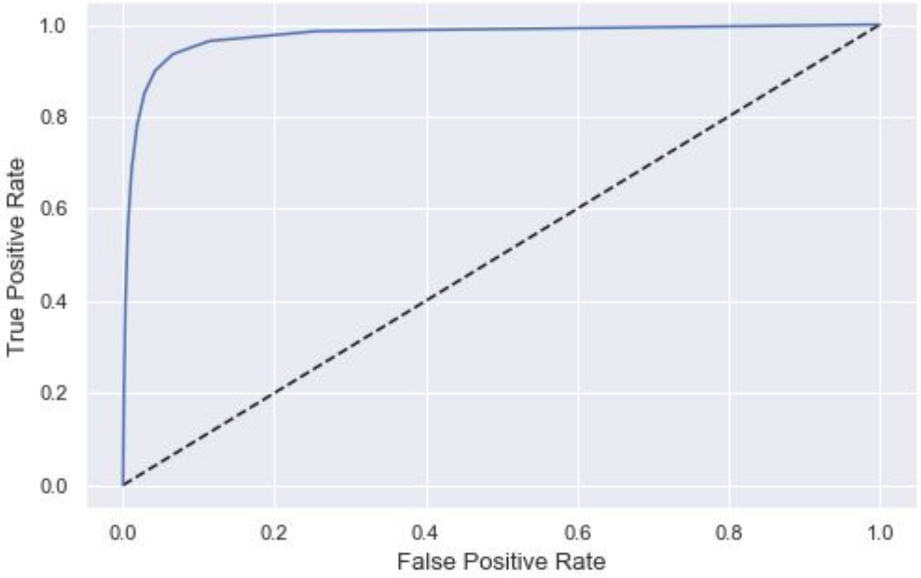
Avg Precision: 0.94

Avg Recall: 0.94

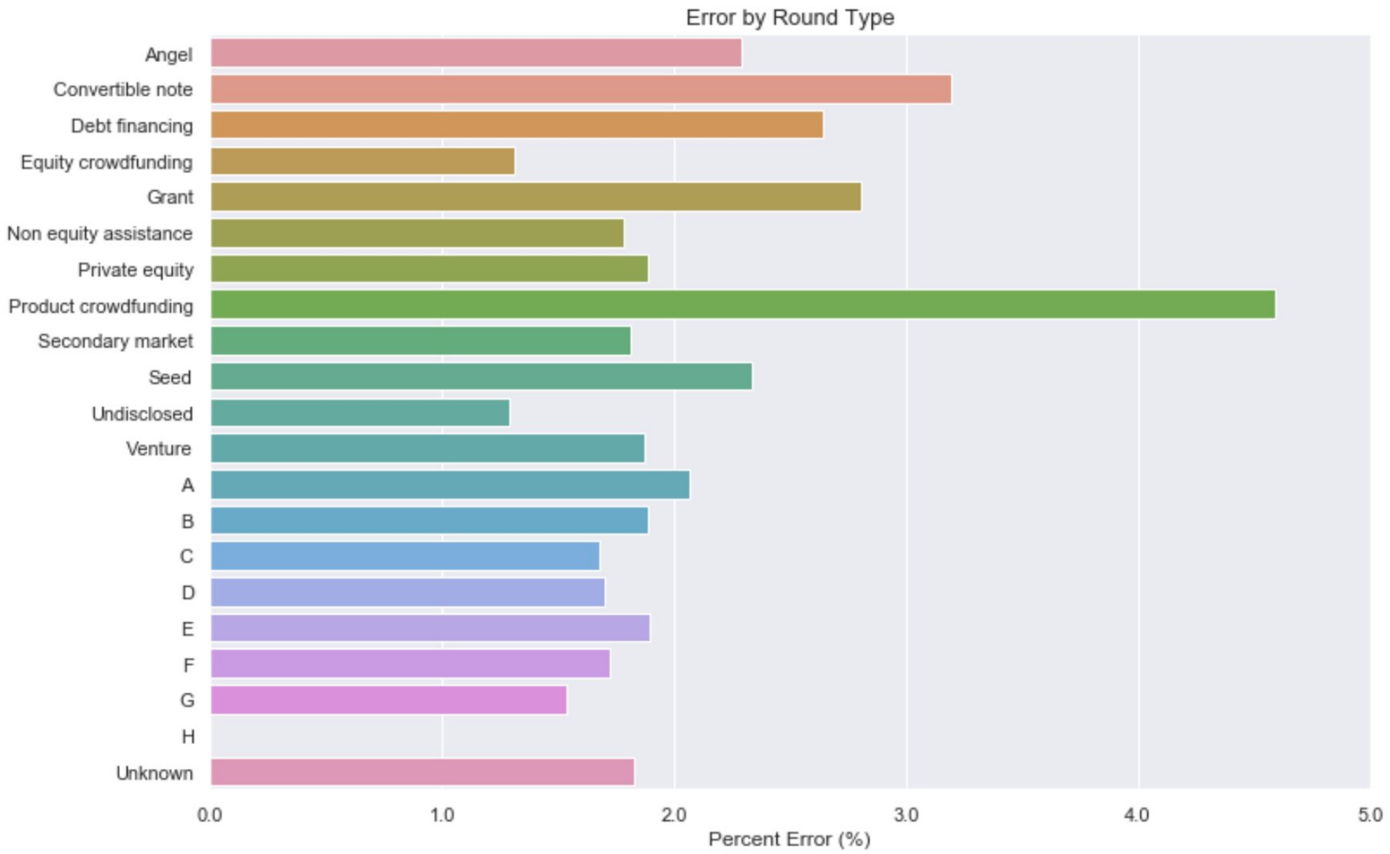
ROC Curve: *Figure on Left*

AUC Score: 0.975

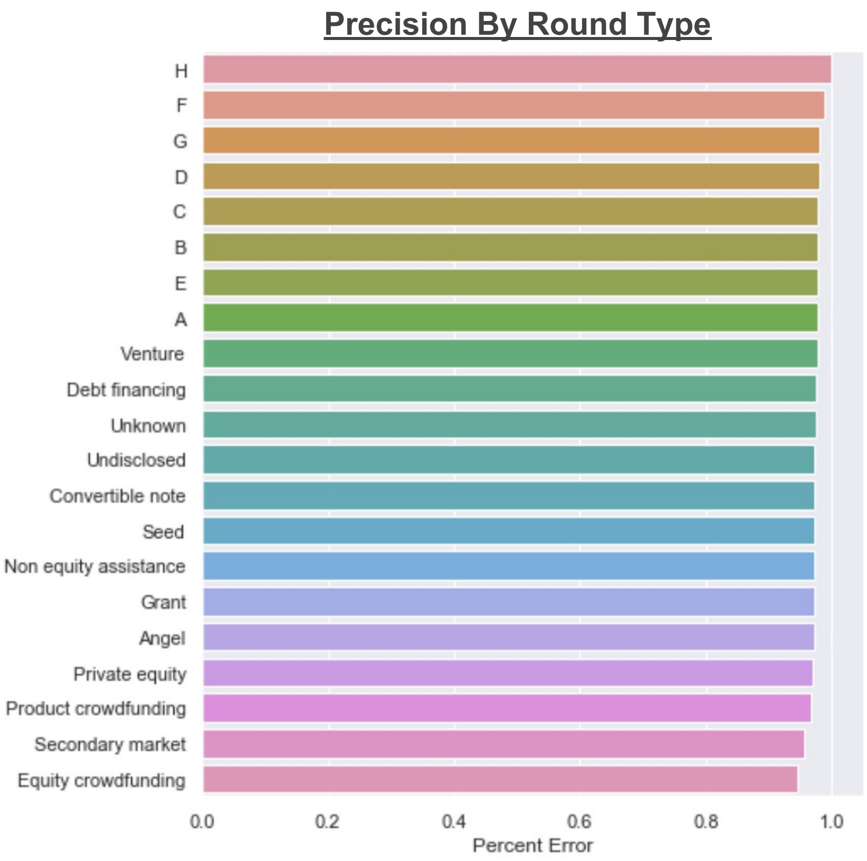
Random Forest ROC Curve

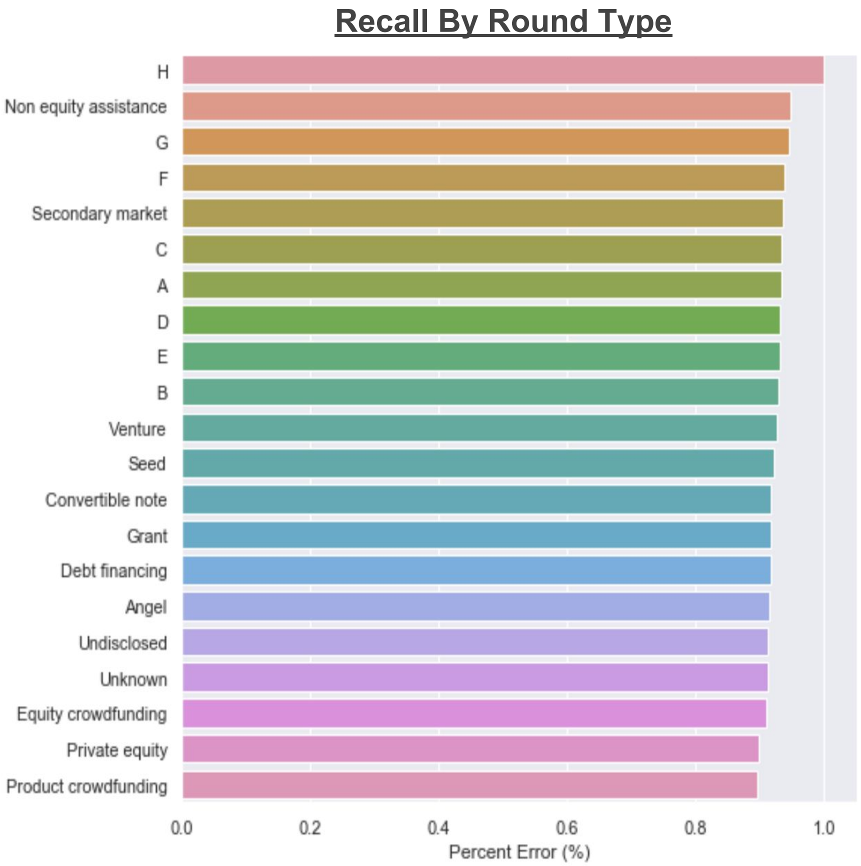


Error by Funding Type



Precision & Recall by Round Type



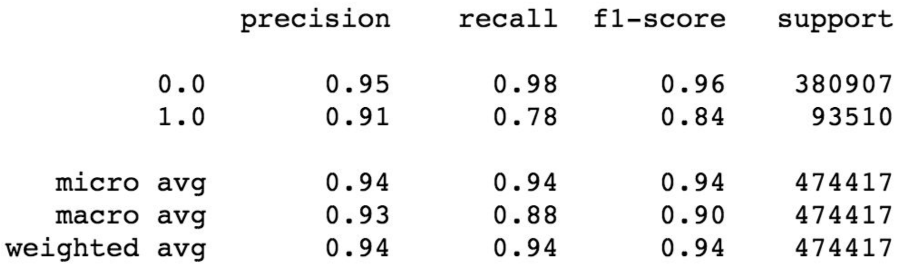


Analyzing Results

Model Had Some Problems With Recalling Funded Targets.

Precision: 91% of Predicted Funded Were Actually Funded.

Recall: 78% of Actual Funded Rounds Were Identified as Funded.



```
              precision    recall  f1-score   support

         0.0       0.95      0.98      0.96    380907
         1.0       0.91      0.78      0.84     93510

   micro avg       0.94      0.94      0.94    474417
   macro avg       0.93      0.88      0.90    474417
weighted avg       0.94      0.94      0.94    474417
```

Precision Or Recall?

In this case, Precision IS *more important* than Recall.

We would rather fund a company and be correct than fund all the correct companies.

(If not fund then at least find)

Outcome

We Were Able To Build a Random Forest Classifier That Predicts Company Funding At *About 94% Accuracy*.

References and Resources

GitHub Repository

https://github.com/daikiminaki/Springboard/tree/master/Capstone_Project_Crunchbase_Funding

Detailed Report

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