IDENTIFYING FAKE JOB POSTINGS

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TABLE OF CONTENTS

01

PROJECT OVERVIEW

FAKE JOB POSTINGS

When people are looking through different sites to find the most interesting job postings according to their professional objectives, they may encounter various job postings and send personal information such as resumé, contact information and even social security number to further proceedings regarding job interviews.

Nonetheless, though rare, there is a risk that the job posting might be fake. Consequently, personal information is at stake.

Therefore, this project aims to identify fake job postings in order to reduce the risk of being the victim of fraud and potentially identity theft .

How Will We Determine Success?

- 95% of data is as not fraudulent.
- Accuracy > 95% will be considered a success.
- Small amount of success is still important because personal information is at stake.
- We would rather false positives due to the serious nature of the problem.

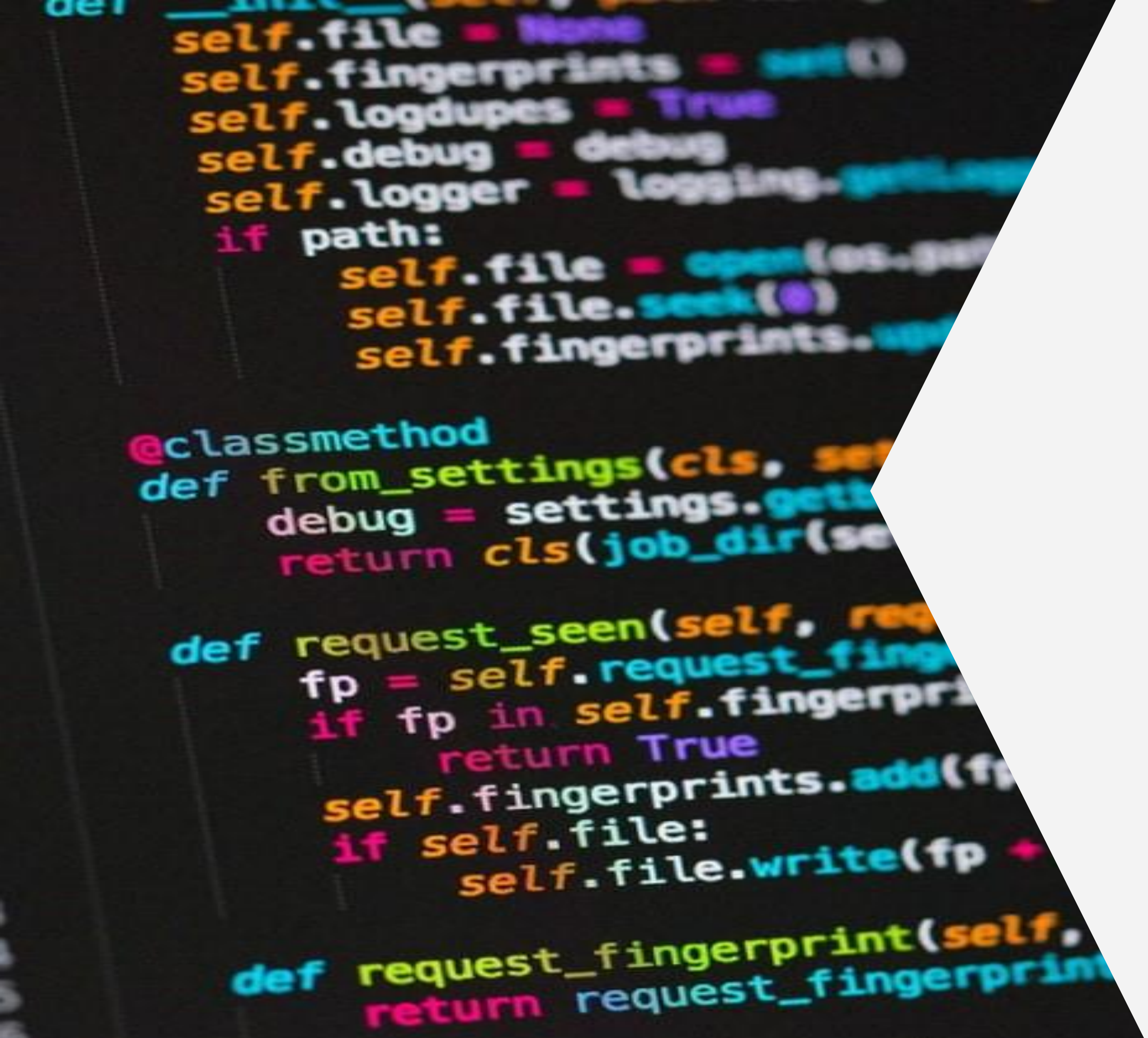
ASSUMPTIONS

Variables measured at a nominal level

Data set is representative of the whole population

Variables consist of two or more categorical independent groups

Missing values indicate that they were not included in the job listing


self.file = None
self.logdupes = True
self.debug = debug
if path:
@classmethod
def from_settings(cls,
debug = settings.
return cls(job_dir(
def request_seen(self,
fp = self.request_
if fp in self.fingerpr
return True
self.fingerprints.add(
if self.file:
self.file.write(fp
def request_fingerprint(self,
return request_fingerprin

02

DATASET

FAKE JOB DATA

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17880 entries, 0 to 17879
Data columns (total 18 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   job_id               17880 non-null  int64
 1   title                17880 non-null  object
 2   location             17534 non-null  object
 3   department           6333 non-null   object
 4   salary_range         2868 non-null   object
 5   company_profile      14572 non-null  object
 6   description          17879 non-null  object
 7   requirements         15185 non-null  object
 8   benefits             10670 non-null  object
 9   telecommuting        17880 non-null  int64
 10  has_company_logo     17880 non-null  int64
 11  has_questions        17880 non-null  int64
 12  employment_type      14409 non-null  object
 13  required_experience  10830 non-null  object
 14  required_education   9775 non-null   object
 15  industry             12977 non-null  object
 16  function             11425 non-null  object
 17  fraudulent           17880 non-null  int64
dtypes: int64(5), object(13)
memory usage: 2.5+ MB
```

Overview

- **From The University of the Aegean**
- **17880 Observations**
- **18 Variables**
- **Dependent Variable: ‘fraudulent’**
- **Only 1 Missing Value for Description(IV)**
- **Other Variables Missing Lots of Data**

GOOD DATASET?

For our purposes, this data set is good. Since our Independent Variable, ‘Description’ , is only missing 1 value and our dependent variable, ‘Fraudulent’, is missing no values, we are considering this a good, clean data set.

DATA WRANGLING

- Not much Data Wrangling needed
- Replaced NaN with ‘’
- Only 1 missing Description
- Drop excess columns

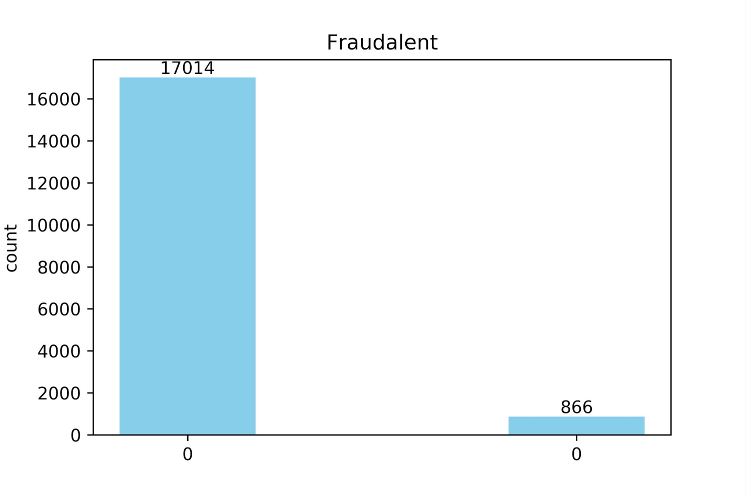
```
6   description              17879 non-null   object
```

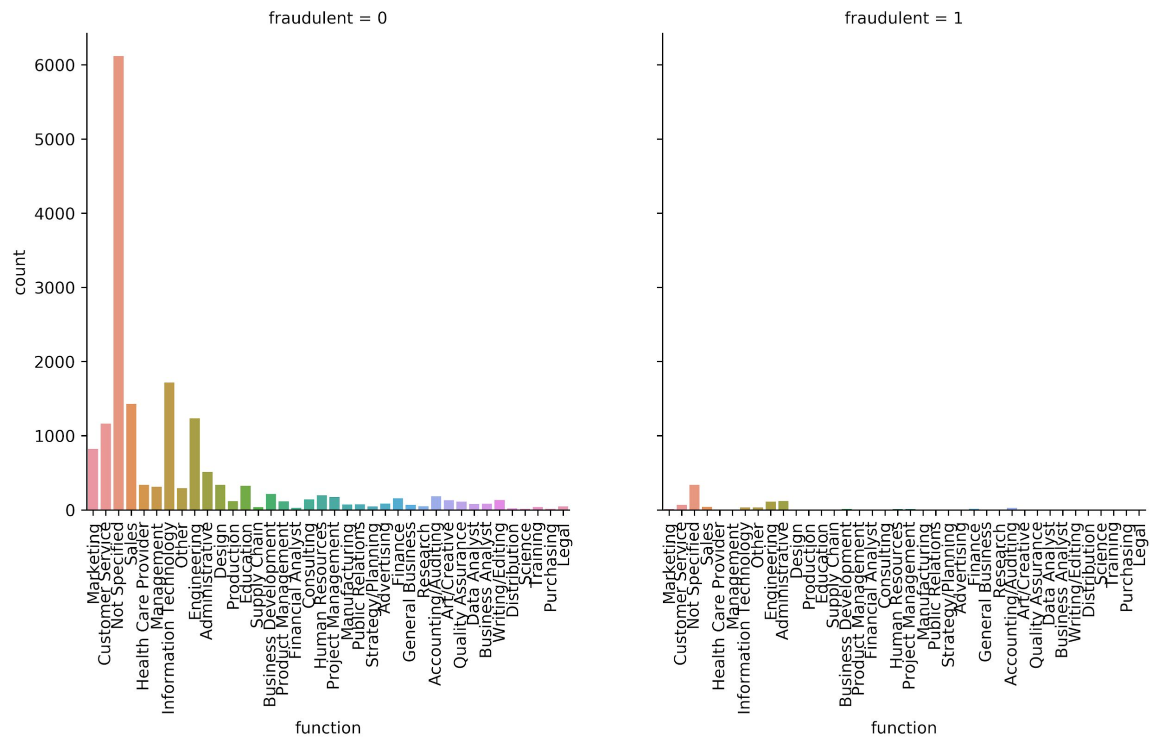
```
#replacing the NaN with blank string for NLP
df_job.replace(np.NaN, '',inplace = True)
```

```
6   description              17880 non-null   object
```

```
#dropping the columns that we are not going to run through the NLP
df_job = df_job.drop(['location','department', 'salary_range', 'telecommuting', 'has_company_logo', 'has_questions', 'employment_type',
'required_experience', 'required_education', 'industry', 'function'], axis = 1)
```

VISUALS


Fraudalent
17014
866
count
0
0

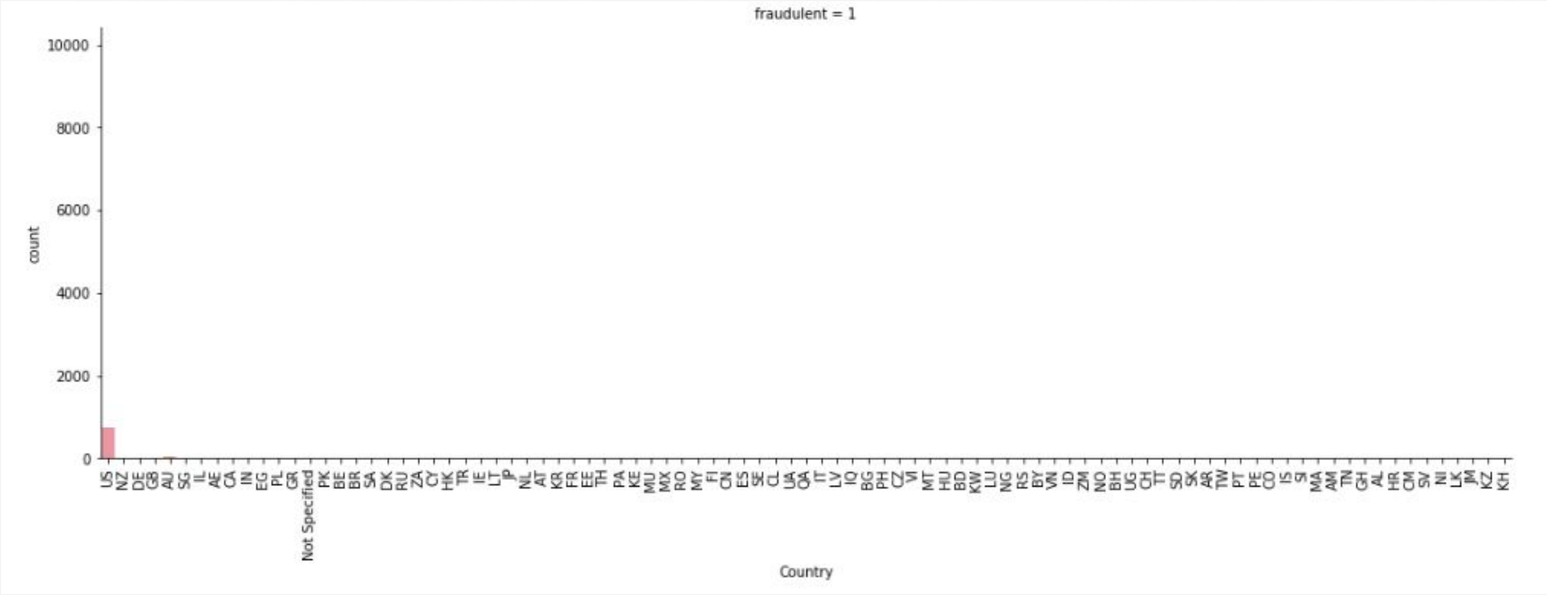

fraudulent = 0
fraudulent = 1
count
function
Marketing
Customer Service
Not Specified
Sales
Health Care Provider
Management
Information Technology
Other
Engineering
Administrative
Design
Production
Education
Supply Chain
Business Development
Product Management
Financial Analyst
Consulting
Human Resources
Project Management
Manufacturing
Public Relations
Strategy/Planning
Advertising
Finance
General Business
Research
Accounting/Auditing
Art/Creative
Quality Assurance
Data Analyst
Business Analyst
Writing/Editing
Distribution
Science
Training
Purchasing
Legal

USA 1° in fraudulent job postings

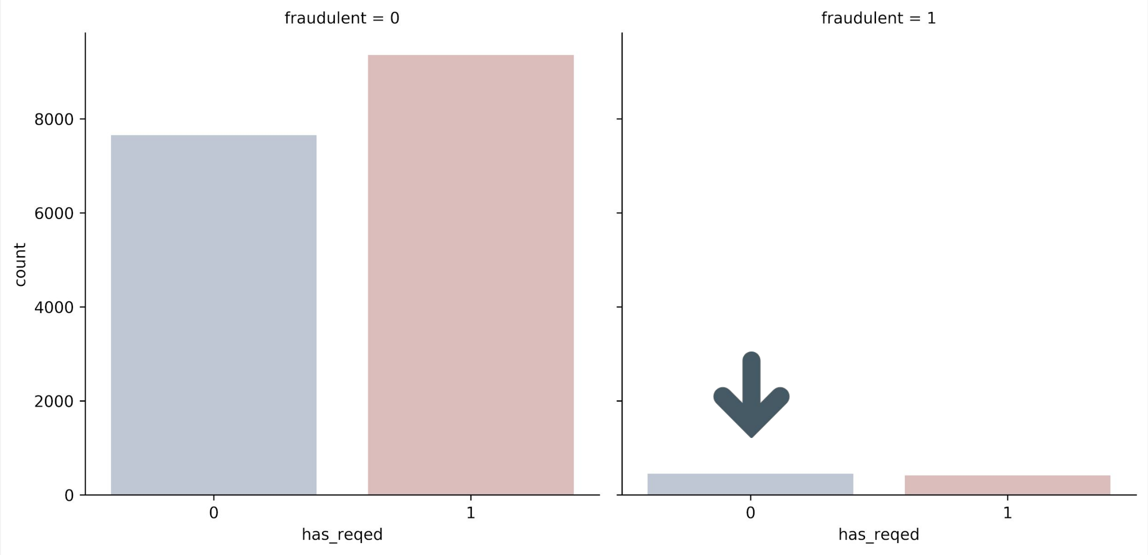
84.3%

4.6%

2.7%



VISUALS



For future investigations…

More sampling of fake job postings could determine if not posting required education is key to classify.

has_reqed	0	1
fraudulent		
0	7654	9360
1	451	415

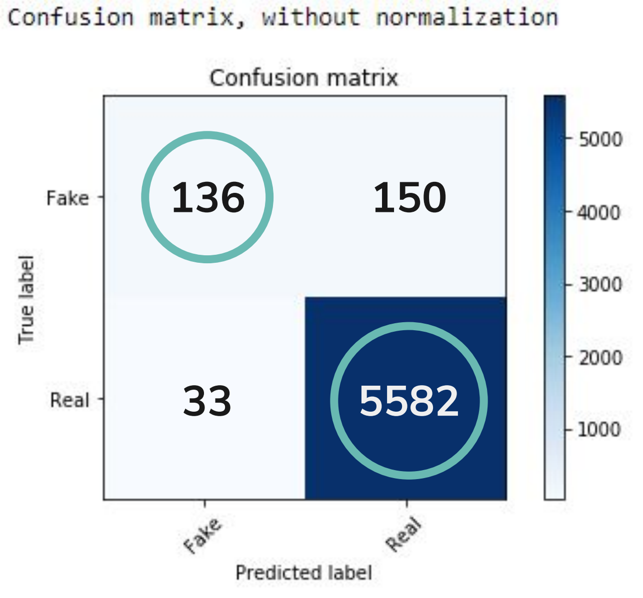
03

MODELING

NATURAL LEARNING PROCESS

PREDICTION SCORE

.9690



***Random state = 25

Example Code

```
X_train, X_test, y_train, y_test = train_test_split(df_job['description'], y, test_size=0.33, random_state=53, stratify = y)
```

```
# Create bag-of-word vectors for the news articles
# https://scikit-learn.org/stable/modules/feature_extraction.html#text-feature-extraction
count_vectorizer = CountVectorizer(stop_words='english')
count_train = count_vectorizer.fit_transform(X_train)
count_test = count_vectorizer.transform(X_test)
```

```
# Instantiate a Multinomial Naive Bayes classifier: nb_classifier
nb_classifier = MultinomialNB()

# Fit the classifier to the training data
nb_classifier.fit(count_train, y_train)

# Create the predicted tags: pred
pred = nb_classifier.predict(count_test)

# Calculate the accuracy score: score
score = metrics.accuracy_score(y_test, pred)
print(score)

# Calculate the confusion matrix: cm
cm = metrics.confusion_matrix(y_test, pred, labels=[1,0])
print(cm)
```

```
0.963226571767497
```

Example Code

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X_train, X_test, y_train, y_test = train_test_split(df_job['description'], y, test_size=0.33, random_state=25, stratify = y)
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```

```
0.9689883070665989
```

04

INSIGHTS

Insights From Model

Success!

Using NLP model we can better predict job listing fraud.

95% -> 96.9% accuracy

This model can be used to classify jobs as fake/real

Description as the best variable for classifying

Other Models Tried

- NLP using Company Profile
- NLP using Requirements
- NLP using benefits
- Random Forest using dummy coded variables
- Decision Tree using dummy coded variables
- Logistic Regression

Personal Insights

- Caroline
  - Get creative! There are so many ways to get interesting insights. Do the research and learn new ways to create models. Even if the models are not successful, thinking outside the box will help me learn more.
- Carter
  - I thought that is was very interesting that the benefits column was such a high performer. If done again, I would like to try to incorporate salary range to see if fraudulent job postings are advertising a certain structure to their salary and benefits package as an incentive to get people to apply.
- Hilda
  - I was very surprised that industrialized countries had the more fake job postings than the most corrupt countries in the world! Personally, I think it is due to lack of sampling on those countries. So, I would get more sampling on fake job postings to corroborate this insight. Also, I would include in which sites are the fake job postings are advertised and accounts of enterprises that contact you through different platforms. This would help visualize which platforms need more security and help identify which sites are preferred to advertise fake job postings.

THANKS

Does anyone have any questions?