PREDICTING FRAUDULENT JOB ADVERTISEMENTS USING LOGISTIC REGRESSION

A Capstone Project

Submitted to the College of Information Technology

in Partial Fulfillment of the Requirements for the Degree

Master of Science in Data Analytics

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June 3, 2021

ABSTRACT

A job advertisement scam is a fraudulent job advertisement typically found on the internet whose purpose is to steal money, obtain personal information, or harm the applicant in some way. There are serious consequences to falling victim to a job advertisement scam including financial loss, identity theft, and damaged reputations. In this study, a logistic regression model is constructed to predict whether a job advertisement is fraudulent based on various features of the advertisement. The model is developed using the Employment Scam Aegean Dataset, a publicly available dataset of 17,880 online job advertisements published between 2012 and 2014 that were classified as legitimate or fraudulent by researchers at the University of the Aegean. The final model identifies 15 job advertisement features as being statistically significant predictors of fraudulent status at the 5% significance level. In addition, a set of six guidelines to help the public avoid job advertisement scams is provided.

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INTRODUCTION

Context

Now more than ever, finding a job is an online process. Within the United States, a 2015 survey by the Pew Research Center found that 54% of Americans have researched jobs on the internet and 45% have applied for a job online (Maurer, 2015). The number of Americans using the internet to research and apply for jobs continues to grow, especially during the ongoing COVID-19 pandemic when millions of Americans have lost their jobs and are seeking new employment (Reinicke, 2020).

Even though it is convenient to search for jobs online, one of the drawbacks is the threat of falling victim to a job advertisement scam. A job advertisement scam is a fraudulent job advertisement typically found on the internet whose purpose is to steal money, obtain personal information, or harm the applicant in some way. Common tactics used by job advertisement scams include but are not limited to:

- Requiring applicants to pay fees to submit an application for a job that doesn't exist.
- Asking applicants to send resumés with personal information to untrustworthy sources.
- Tricking applicants into downloading malicious job application software containing computer viruses or malware.

The problems caused by job advertisement scams (financial loss, identity theft, damaged reputations, etc.) are serious enough that researchers are working to identity their common attributes and educate the general public about how to avoid them (Vidros et al., 2017).

Research Question

The research question for the study is: "Which features of a job advertisement can help identify whether the advertisement is fraudulent?" Following in the footsteps of (Vidros et al., 2017), (Alghamdi & Alharby, 2019) and (Kumar, 2020), the goal of the study is to create a model that will predict whether a job advertisement is fraudulent based on various features of the advertisement. In particular, the study will use logistic regression, a classic modeling technique for predicting the value of a binary target variable like fraudulent status (Patetta, Lesson 2.1). Once the logistic regression model has been created, it will be possible to answer the research question by examining the most statistically significant predictor variables in the model. The study will be beneficial to the general public because it will provide insights into the common features of job advertisement scams and give guidance for how to avoid them.

Hypotheses

The following null hypothesis H_0 and alternative hypothesis H_a will be used when constructing the logistic regression model:

> H_0: There is no statistically significant association between the job advertisement features in the study and the probability of the advertisement being fraudulent.
>
> H_a: There is a statistically significant association between at least one of the job advertisement features in the study and the probability of the advertisement being fraudulent.

It is expected that the null hypothesis H_0 will be rejected in favor of the alternative hypothesis H_a because the model will incorporate a wide variety of job advertisement features and the probability that none of them are significant is low. However, which features specifically are significant remains to be determined.

DATA COLLECTION

The Employment Scam Aegean Dataset

The logistic regression model will be developed using the Employment Scam Aegean Dataset (EMSCAD), a collection of 17,880 online job advertisements published between 2012 to 2014 which were collected by the University of the Aegean in Greece. Of the 17,880 job advertisements in the dataset, 17,014 are classified as legitimate and 866 are classified as fraudulent. The dataset is publicly available and can be downloaded as a CSV file from the University of the Aegean website.[1] The dataset has also been investigated by data scientists on Kaggle and can be downloaded there as well.[2] No particular methodology was needed to collect the data since this step was already completed by the researchers at the University of the Aegean when they assembled the EMSCAD.

List of Original Variables

Table 1: List of variables in the original Employment Scam Aegean Dataset.

Variable Name	Type	Description
job_id	Numeric, discrete	ID number assigned to job advertisement. Equivalent to row number in dataset.
title	Character	Job title.
location	Character	Geographical location of job. Format: Country, Province, City.
department	Character	Internal department of company. (Ex: Marketing, Sales, etc.)
salary_range	Character	Lower & upper bounds for salary. (Ex: $20,000-$28,000)
company_profile	Text	Company profile.
description	Text	Job description.
requirements	Text	Eligibility requirements for job.
benefits	Text	List of job benefits.
telecommuting	Numeric, binary	True for telecommuting/work-from-home positions.

[1] http://emscad.samos.aegean.gr/

[2] https://www.kaggle.com/shivamb/real-or-fake-fake-jobposting-prediction

has_company_logo	Numeric, binary	True if company logo is visible in job advertisement.
has_questions	Numeric, binary	True if job advertisement has screening questions.
employment_type	Categorical	Employment type. (Ex: Full-time, part-time, etc.)
required_experience	Categorical	Prior experience required for job. (Ex: Entry level, executive, etc.)
required_education	Categorical	Education level required for job. (Ex: Bachelor's Degree, Master's Degree, etc.)
industry	Categorical	Industry company belongs to. (Ex: Telecommunications, financial services, etc.)
function	Categorical	Nature of job. (Ex: Sales, Engineering, etc.)
fraudulent	Numeric, binary	True if job advertisement is fraudulent.

Variables 2-17 (*title*, *location*, *department*, *salary_range*, *company_profile*, *description*, *requirements*, *benefits*, *telecommuting*, *has_company_logo*, *has_questions*, *employment_type*, *required_experience*, *required_education*, *industry*, *function*) are independent variables that will be used to predict the value of Variable 18, *fraudulent*, the binary dependent variable that is the focus of the study. However, one of the challenges presented by the EMSCAD is that logistic regression models only accept numeric variables or categorical variables encoded with dummy variables as inputs (Patetta, Lesson 3.2), and some of the independent variables are character or text variables. To address this issue, the study will adopt a similar approach as (Vidros et al., 2017) and create new numeric variables based on the information provided by the character and text variables which can then be used in the model.

DATA PREPARATION AND EXTRACTION

Tools and Techniques

The majority of the analysis will be carried out using SAS OnDemand for Academics, a free cloud version of SAS Studio for university students and professors. SAS is a statistical software suite that has been a data science industry standard for decades (Goled, 2020). SAS is an appropriate choice of software for the study because it provides all of the necessary tools for processing the data, making graphs and charts, and creating logistic regression models. However, a small but significant portion of the analysis will be performed outside of SAS using the popular object-oriented programming language Python. In particular, the character variable *title* and the text variables *company_profile*, *description*, *requirements*, and *benefits* will undergo text mining with Python's Natural Language Tool Kit (NLTK) to create new numeric variables which can be used in the logistic regression model since the original character and text variables cannot be used directly themselves. SAS does have its own text mining software called SAS Text Miner, but it is not free and open-source like Python's NLTK library.

Exploring the Data

In SAS Studio, the first step was to create a project library called "capstone" and import the EMSCAD CSV file as a SAS table:

```
/* Create project library */

libname capstone "&path";

/* Import data */

proc import datafile="&path/EMSCAD.csv"
            dbms=csv
            out=capstone.EMSCAD;
      guessingrows=max;
run;
```

Next, the data sparsity was investigated using the following code from (Wicklin, 2011):

```
/* Create missing/not missing format */

proc format;
      value $missfmt ' '='Missing' other='Not Missing';
      value  missfmt  . ='Missing' other='Not Missing';
run;

/* View missing/not missing statistics for each variable */

proc freq data=capstone.EMSCAD;
      format _CHAR_ $missfmt.;
      tables _CHAR_ / missing missprint nocum;
      format _NUMERIC_ missfmt.;
      tables _NUMERIC_ / missing missprint nocum;
run;

/* Overall data sparsity */

%let all_vars=job_id, title, location, department, salary_range,
              company_profile, description, requirements, benefits,
              telecommuting, has_company_logo, has_questions, employment_type,
              required_experience, required_education, industry, function,
              fraudulent;
proc sql;
      select sum(cmiss(&all_vars))/(17880*18)
      as 'Overall sparsity'n
      from capstone.EMSCAD;
quit;
```

The results are summarized in Table 2.

Table 2: Data sparsity results.

Variable Name	Missing (Count)	Missing (Percent)	Not Missing (Count)	Not Missing (Percent)
job_id	0	0	17880	100
title	0	0	17880	100
location	346	1.94	17534	98.06
department	11553	64.61	6327	35.39
salary_range	15012	83.96	2868	16.04
company_profile	3308	18.50	14572	81.50
description	0	0	17880	100
requirements benefits	2696 7206	15.08 40.30	15184 10674	84.92 59.70
telecommuting	0	0	17880	100
has_company_logo	0	0	17880	100
has_questions	0	0	17880	100
employment_type	3471	19.41	14409	80.59

required_experience	7050	39.43	10830	60.57
required_education	8105	45.33	9775	54.67
industry	4903	27.42	12977	72.58
function	6455	36.10	11425	63.90
fraudulent	0	0	17880	100
Overall sparsity: 21.78%				

From Table 2, we can see that the variables *job_id*, *title*, *description*, *telecommuting*, *has_company_logo*, *has_questions* and *fraudulent* have no missing values, the variables *location*, *company_profile*, *requirements*, *benefits*, *employment_type*, *required_experience*, *required_education*, *industry*, and *function* have some missing values (below 50%), and the variables *department* and *salary_range* have many missing values (at least 60%). Overall, the dataset is 78.22% occupied, 21.78% sparse. The missing values in the dataset will be addressed in the next section, Cleaning the Data.

Next, the categorical variables *employment_type*, *required_experience*, *required_education*, *industry*, and *function* were explored in more detail:

```
/* Inspect raw categorical variables */

%let cat_vars=employment_type required_experience required_education
              industry function;

proc freq data=capstone.EMSCAD order=freq;
      tables &cat_vars;
run;
```

The results of the FREQ procedure are shown in Tables 3-7.

Table 3: PROC FREQ results for *employment_type*.

Category	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Full-time	11620	80.64	11620	80.64
Contract	1524	10.58	13144	91.22
Part-time	797	5.53	13941	96.75

Temporary	241	1.67	14182	98.42
Other	227	1.58	14409	100.00
Frequency Missing: 3471				

Table 4: PROC FREQ results for *required_experience*.

Category	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Mid-Senior level	3809	35.17	3809	35.17
Entry level	2697	24.90	6506	60.07
Associate	2297	21.21	8803	81.28
Not Applicable	1116	10.30	9919	91.59
Director	389	3.59	10308	95.18
Internship	381	3.52	10689	98.70
Executive	141	1.30	10830	100.00
Frequency Missing: 7050				

Table 5: PROC FREQ results for *required_education*.

Category	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Bachelor's Degree	5145	52.63	5145	52.63
High School or equivalent	2080	21.28	7225	73.91
Unspecified	1397	14.29	8622	88.20
Master's Degree	416	4.26	9038	92.46
Associate Degree	274	2.80	9312	95.26
Certification	170	1.74	9482	97.00
Some College Coursework Completed	102	1.04	9584	98.05
Professional	74	0.76	9658	98.80
Vocational	49	0.50	9707	99.30
Some High School Coursework	27	0.28	9734	99.58
Doctorate	26	0.27	9760	99.85
Vocational - HS Diploma	9	0.09	9769	99.94
Vocational - Degree	6	0.06	9775	100.00
Frequency Missing: 8105				

Table 6: PROC FREQ results for *industry*.

Category	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Information Technology and Services	1734	13.36	1734	13.36
Computer Software	1376	10.60	3110	23.97
Internet	1062	8.18	4172	32.15
Marketing and Advertising	828	6.38	5000	38.53
Education Management	822	6.33	5822	44.86
Financial Services	779	6.00	6601	50.87
Hospital & Health Care	497	3.83	7098	54.70
Consumer Services	358	2.76	7456	57.46
Telecommunications	342	2.64	7798	60.09
Oil & Energy	287	2.21	8085	62.30
Retail	223	1.72	8308	64.02
Real Estate	175	1.35	8483	65.37
Accounting	159	1.23	8642	66.59
Construction	158	1.22	8800	67.81
E-Learning	139	1.07	8939	68.88
Management Consulting	130	1.00	9069	69.89
Design	129	0.99	9198	70.88
Health, Wellness and Fitness	127	0.98	9325	71.86
Staffing and Recruiting	127	0.98	9452	72.84
Insurance	123	0.95	9575	73.78
Automotive	120	0.92	9695	74.71
Logistics and Supply Chain	112	0.86	9807	75.57
Human Resources	108	0.83	9915	76.40
Online Media	101	0.78	10016	77.18
Apparel & Fashion	97	0.75	10113	77.93
Legal Services	97	0.75	10210	78.68
Facilities Services	94	0.72	10304	79.40
Hospitality	88	0.68	10392	80.08
Computer Games	86	0.66	10478	80.74
Banking	84	0.65	10562	81.39
Building Materials	78	0.60	10640	81.99
Leisure, Travel & Tourism	76	0.59	10716	82.58
Nonprofit Organization Management	76	0.59	10792	83.16
Entertainment	74	0.57	10866	83.73
Electrical/Electronic Manufacturing	73	0.56	10939	84.30
Food & Beverages	72	0.55	11011	84.85
Cosmetics	65	0.50	11076	85.35
Airlines/Aviation	63	0.49	11139	85.84

Consumer Goods	63	0.49	11202	86.32
Consumer Electronics	62	0.48	11264	86.80
Medical Practice	60	0.46	11324	87.26
Public Relations and Communications	58	0.45	11382	87.71
Civic & Social Organization	55	0.42	11437	88.13
Market Research	54	0.42	11491	88.55
Transportation/Trucking/Railroad	53	0.41	11544	88.96
Restaurants	52	0.40	11596	89.36
Warehousing	51	0.39	11647	89.75
Broadcast Media	50	0.39	11697	90.14
Events Services	50	0.39	11747	90.52
Computer & Network Security	49	0.38	11796	90.90
Environmental Services	49	0.38	11845	91.28
Media Production	48	0.37	11893	91.65
Computer Networking	44	0.34	11937	91.99
Food Production	44	0.34	11981	92.32
Gambling & Casinos	42	0.32	12023	92.65
Pharmaceuticals	42	0.32	12065	92.97
Publishing	39	0.30	12104	93.27
Biotechnology	38	0.29	12142	93.57
Mechanical or Industrial Engineering	37	0.29	12179	93.85
Computer Hardware	35	0.27	12214	94.12
Utilities	33	0.25	12247	94.37
Graphic Design	32	0.25	12279	94.62
Printing	30	0.23	12309	94.85
Security and Investigations	30	0.23	12339	95.08
Research	29	0.22	12368	95.31
Venture Capital & Private Equity	29	0.22	12397	95.53
Information Services	28	0.22	12425	95.75
Aviation & Aerospace	24	0.18	12449	95.93
Farming	24	0.18	12473	96.12
Mental Health Care	23	0.18	12496	96.29
Sports	23	0.18	12519	96.47
Chemicals	22	0.17	12541	96.64
Government Administration	22	0.17	12563	96.81
Law Practice	19	0.15	12582	96.96
Medical Devices	19	0.15	12601	97.10
Outsourcing/Offshoring	19	0.15	12620	97.25
Writing and Editing	19	0.15	12639	97.40
Business Supplies and Equipment	18	0.14	12657	97.53
Fund-Raising	16	0.12	12673	97.66

Professional Training & Coaching	14	0.11	12687	97.77
Government Relations	11	0.08	12698	97.85
Higher Education	11	0.08	12709	97.93
Machinery	11	0.08	12720	98.02
Semiconductors	11	0.08	12731	98.10
Wholesale	11	0.08	12742	98.19
Architecture & Planning	10	0.08	12752	98.27
Law Enforcement	10	0.08	12762	98.34
Music	10	0.08	12772	98.42
Translation and Localization	10	0.08	12782	98.50
Civil Engineering	9	0.07	12791	98.57
Defense & Space	9	0.07	12800	98.64
Individual & Family Services	9	0.07	12809	98.71
Program Development	9	0.07	12818	98.77
Renewables & Environment	9	0.07	12827	98.84
Executive Office	8	0.06	12835	98.91
International Trade and Development	8	0.06	12843	98.97
Veterinary	8	0.06	12851	99.03
Industrial Automation	7	0.05	12858	99.08
Photography	7	0.05	12865	99.14
Public Safety	7	0.05	12872	99.19
Investment Management	6	0.05	12878	99.24
Motion Pictures and Film	6	0.05	12884	99.28
Primary/Secondary Education	6	0.05	12890	99.33
Religious Institutions	6	0.05	12896	99.38
Animation	5	0.04	12901	99.41
Capital Markets	5	0.04	12906	99.45
Import and Export	5	0.04	12911	99.49
Package/Freight Delivery	5	0.04	12916	99.53
Packaging and Containers	5	0.04	12921	99.57
Commercial Real Estate	4	0.03	12925	99.60
Fishery	4	0.03	12929	99.63
Investment Banking	4	0.03	12933	99.66
Luxury Goods & Jewelry	4	0.03	12937	99.69
Philanthropy	4	0.03	12941	99.72
Wireless	4	0.03	12945	99.75
Furniture	3	0.02	12948	99.78
Maritime	3	0.02	12951	99.80
Mining & Metals	3	0.02	12954	99.82
Performing Arts	3	0.02	12957	99.85
Plastics	3	0.02	12960	99.87
Public Policy	3	0.02	12963	99.89
Libraries	2	0.02	12965	99.91

Military	2	0.02	12967	99.92
Nanotechnology	2	0.02	12969	99.94
Textiles	2	0.02	12971	99.95
Alternative Dispute Resolution	1	0.01	12972	99.96
Museums and Institutions	1	0.01	12973	99.97
Ranching	1	0.01	12974	99.98
Shipbuilding	1	0.01	12975	99.98
Sporting Goods	1	0.01	12976	99.99
Wine and Spirits	1	0.01	12977	100.00
Frequency Missing: 4903				

Table 7: PROC FREQ results for *function*.

Category	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Information Technology	1749	15.31	1749	15.31
Sales	1468	12.85	3217	28.16
Engineering	1348	11.80	4565	39.96
Customer Service	1229	10.76	5794	50.71
Marketing	830	7.26	6624	57.98
Administrative	630	5.51	7254	63.49
Design	340	2.98	7594	66.47
Health Care Provider	338	2.96	7932	69.43
Education	325	2.84	8257	72.27
Other	325	2.84	8582	75.12
Management	317	2.77	8899	77.89
Business Development	228	2.00	9127	79.89
Accounting/Auditing	212	1.86	9339	81.74
Human Resources	205	1.79	9544	83.54
Project Management	183	1.60	9727	85.14
Finance	172	1.51	9899	86.64
Consulting	144	1.26	10043	87.90
Art/Creative	132	1.16	10175	89.06
Writing/Editing	132	1.16	10307	90.21
Production	116	1.02	10423	91.23
Product Management	114	1.00	10537	92.23
Quality Assurance	111	0.97	10648	93.20
Advertising	90	0.79	10738	93.99
Business Analyst	84	0.74	10822	94.72
Data Analyst	82	0.72	10904	95.44
Public Relations	76	0.67	10980	96.11

Manufacturing	74	0.65	11054	96.75
General Business	68	0.60	11122	97.35
Research	50	0.44	11172	97.79
Legal	47	0.41	11219	98.20
Strategy/Planning	46	0.40	11265	98.60
Training	38	0.33	11303	98.93
Supply Chain	36	0.32	11339	99.25
Financial Analyst	33	0.29	11372	99.54
Distribution	24	0.21	11396	99.75
Purchasing	15	0.13	11411	99.88
Science	14	0.12	11425	100.00
Frequency Missing: 6455				

From Tables 3-7, we can see that *employment_type* has five categories with the most frequent category being "Full-time", *required_experience* has seven categories with the most frequent category being "Mid-Senior level", and *required_education* has 13 categories with the most frequent category being "Bachelor's Degree." However, some of the categories of *required_education* are redundant. In particular, there are multiple categories of the "Vocational" type; it would be logical to merge these categories. As for the categorical variables *industry* and *function*, *industry* has 131 categories with the most frequent category being "Information Technology and Services" while *function* has 37 categories with the most frequent category being "Information Technology."

Cleaning the Data

It is clear that several variables in the EMSCAD need to be cleaned. In particular, the following changes will be made:

- The character variable *location* stating the country, province and city of the job is too specific. Instead, only the country portion will be kept as a new categorical variable called *country*.

- The character variable *salary_range* has too many missing values (83.96% according to Table 2) for the actual salary ranges to be useful. Instead, it will be replaced by a binary variable *mentions_salary* which is true if salary is mentioned in the job advertisement or false if salary is not mentioned.
- All categories of the "Vocational" type for the categorical variable *required_education* will be merged into a single category. Also, the categories "Some High School Coursework" and "High School or equivalent" will be merged since these two categories are similar.
- Missing values for the categorical variables *employment_type*, *required_experience*, *required_education*, *industry*, *function*, and *country* will be assigned the category "Unspecified".
- The character variable *department* will be dropped because it is similar to the categorical variable *function* but has a higher sparsity (*department* is 64.61% sparse compared to *function* which is only 36.10% sparse according to Table 2).
- The character variable *title* and the text variables *company_profile*, *description*, *requirements*, and *benefits* will be dropped from the dataset. These variables are dealt with separately in the Text Mining section.

Here is the SAS code that was used to make these changes. The results were saved as a new SAS table called "EMSCAD_clean".

```
/* Clean data */

data capstone.EMSCAD_clean;
	retain job_id country employment_type required_experience
		required_education industry function mentions_salary
		telecommuting has_company_logo has_questions fraudulent;
	length employment_type $15.;
	format employment_type $15.;
	set capstone.EMSCAD;
```

```
/* Extract country from location */
      country=scan(location, 1);
/* Salary indicator */
      if missing(salary_range) then mentions_salary=0;
      else mentions_salary=1;
/* Clean categories of required_education */
      if required_education =: 'Vocational' then
            required_education='Vocational';
      else if required_education =: 'Some High School' then
            required_education='High School or equivalent';
/* Address missing values */
      array x{*} country &cat_vars;
      do _n_=1 to dim(x);
            if missing(x{_n_}) then x{_n_}='Unspecified';
      end;
/* Drop unnecessary columns */
      drop title location department salary_range company_profile description
           requirements benefits;
run;
```

Another modification which will improve the appearance of certain graphs later on is reordering the levels of the categorical variables so that they appear in a more natural order. In particular, the categories of *employment_type* can be ordered from highest commitment (“Full-time”) to least commitment (“Temporary”), the categories of *required_experience* can be ordered from least experience (“Internship”) to most experience (“Executive”), and the categories of *required_education* can be ordered from least education (“High School or equivalent”) to most education (“Doctorate”). Here is the SAS code to reorder the categorical variable levels:

```
/* Create formats for reordering categorical variable levels */

proc format;
      value etf       1='Full-time'
                      2='Part-time'
                      3='Contract'
                      4='Temporary'
                      5='Other'
                      6='Unspecified';
      value rexf      1='Internship'
                      2='Entry level'
                      3='Associate'
                      4='Mid-Senior level'
                      5='Director'
                      6='Executive'
                      7='Not Applicable'
                      8='Unspecified';
```

```
        value redf      1='High School or equivalent'
                        2='Some college coursework'
                        3='Associate Degree'
                        4="Bachelor's Degree"
                        5="Master's Degree"
                        6='Doctorate'
                        7='Professional'
                        8='Vocational'
                        9='Certification'
                        10='Unspecified';
run;

/* Reorder categorical variable levels */

data capstone.EMSCAD_clean;
        retain job_id country employment_type required_experience
               required_education industry function mentions_salary
               telecommuting has_company_logo has_questions fraudulent;
        format employment_type etf. required_experience rexf.
               required_education redf.;
        set capstone.EMSCAD_clean(rename=(employment_type=et
                                          required_experience=rex
                                          required_education=red));
        select (et);
              when ('Full-time')        employment_type=1;
              when ('Part-time')        employment_type=2;
              when ('Contract')         employment_type=3;
              when ('Temporary')        employment_type=4;
              when ('Other')            employment_type=5;
              when ('Unspecified')      employment_type=6;
        end;
        select (rex);
              when ('Internship')             required_experience=1;
              when ('Entry level')            required_experience=2;
              when ('Associate')              required_experience=3;
              when ('Mid-Senior level')       required_experience=4;
              when ('Director')               required_experience=5;
              when ('Executive')              required_experience=6;
              when ('Not Applicable')         required_experience=7;
              when ('Unspecified')            required_experience=8;
        end;
        select (red);
              when ('High School or equivalent')     required_education=1;
              when ('Some college coursework')       required_education=2;
              when ('Associate Degree')              required_education=3;
              when ("Bachelor's Degree")             required_education=4;
              when ("Master's Degree")               required_education=5;
              when ('Doctorate')                     required_education=6;
              when ('Professional')                  required_education=7;
              when ('Vocational')                    required_education=8;
              when ('Certification')                 required_education=9;
              when ('Unspecified')                   required_education=10;
        end;
        drop et rex red;
run;
```

Collapsing Categorical Variable Levels

The data is now clean, but there are still some potential problems which may arise with the categorical variables. As mentioned earlier, the standard way to incorporate a categorical variable into a logistic regression model is to encode the categories with numeric dummy variables. For categorical variables with a low number of categories such as *employment_type*, *required_experience*, and *required_education*, this process should work fine, but for categorical variables with a high number of categories such as *industry*, *function*, and *country*, creating dummy variables to represent all of the categories is not practical and can lead to problems like high-dimensionality and quasi-complete separation (Patetta, Lesson 3.2). Therefore, it is necessary to collapse the levels of *industry*, *function*, and *country* before these variables can be used in the logistic regression model.

First, cross tabulations of *industry*, *function*, and *country* with *fraudulent* were performed to determine which categories have fraudulent job advertisements and which categories do not:

```
/* Cross tabulations */
proc freq data=capstone.EMSCAD_clean order=freq;
      tables (industry function country)*fraudulent;
run;
```

The results are quite lengthy and are not presented here for brevity's sake (the interested reader may consult the Appendix). The cross tabulation of *country* with *fraudulent* shows that a large majority of fraudulent job advertisements (84.30%) come from the United States. Therefore, the levels of the categorical variable *country* were collapsed by replacing *country* with a binary variable *from_US* which is true if the job advertisement comes from the United States or false if the job advertisement comes from any other country including "Unspecified". Here is the SAS code that was used to create the *from_US* variable:

```
/* United States indicator */

data capstone.EMSCAD_clean;
	set capstone.EMSCAD_clean;
	if country='US' then from_US=1;
	else from_US=0;
run;
```

On the other hand, *industry* and *function* do not possess a single category that dominates the others in terms of how many fraudulent job advertisements exist for that category. Therefore, the levels of the categorical variables *industry* and *function* were collapsed using the smooth weight-of-evidence (SWOE) technique discussed in (Patetta, Lesson 3.2). The SWOE technique converts *industry* and *function* into continuous numeric variables by replacing each category with the smoothed log-odds of the target event for that category, calculated using the formula

$$\ln\left(\frac{\#\text{events} + c\rho_1}{\#\text{non-events} + c(1-\rho_1)}\right)$$

where #events is the number of fraudulent job advertisements for the category, #non-events is the number of legitimate job advertisements for the category, ρ_1 is the proportion of fraudulent job advertisements in the dataset (approximately 4.84%), and c is a smoothing parameter selected by the analyst, chosen to be 1 for the study.[3] Here is the SAS code to perform the SWOE technique on *industry*, storing the results as a new variable called *industry_SWOE*:

```
/* Determine population proportion of fraudulent job ads */

%global rho1;

proc sql;
	select mean(fraudulent) into: rho1
	from capstone.EMSCAD;
quit;
```

[3] In general, the larger the value of c, the more aggressively the data is smoothed (Patetta, Lesson 3.2). The choice of $c = 1$ is relatively small and has a minimal effect on the smoothed log-odds values.

```
/* Count fraudulent job ads per industry */

proc means data=capstone.EMSCAD_clean sum nway;
	class industry;
	var fraudulent;
	output out=work.industry_counts sum=events;
run;

/* Compute industry SWOE */

data work.industry_counts;
	set work.industry_counts;
	industry_SWOE = log((events + &rho1)/(_FREQ_ - events + (1 - &rho1)));
run;
```

The same type of code was used to perform the SWOE technique on *function* and store the results as a new variable called *function_SWOE*. The variables *industry_SWOE* and *function_SWOE* were then added to the "EMSCAD_clean" dataset and the results were saved as a new SAS table called "EMSCAD_clean_SWOE":

```
/* Add industry_SWOE and function_SWOE to dataset */

proc sql;
	create table capstone.EMSCAD_clean_SWOE as
		select E.*, I.industry_SWOE, F.function_SWOE
		from capstone.EMSCAD_clean E
		left join work.industry_counts I
		on E.industry = I.industry
		left join work.function_counts F
		on E.function = F.function
		order by E.job_id;
quit;
```

Text Mining

In this section, we switch to using Python to extract information from the character variable *title* and the text variables *company_profile*, *description*, *requirements*, and *benefits*. First, all necessary functions were imported from the standard data science libraries NumPy, Pandas, Re and Matplotlib as well as the NLTK text mining library:

```
# Import required libraries

import numpy as np
import pandas as pd
import re
import matplotlib.pyplot as plt
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer
from nltk.probability import FreqDist
```

Next, the EMSCAD dataset was read into a Pandas dataframe called “df”, keeping only the variables needed for text mining and replacing any occurrences of NaN with blank strings.

```
# Import data

df = pd.read_csv(path + '/EMSCAD.csv', engine='python')
df.drop(['location', 'department', 'salary_range', 'telecommuting',
         'has_company_logo', 'has_questions', 'employment_type',
         'required_experience', 'required_education', 'industry',
         'function'], inplace=True, axis=1)

# Replace NaNs with blanks

df.fillna(' ', inplace = True)
```

For each job advertisement, the text features *company_profile*, *description*, *requirements*, and *benefits* were tokenized (transformed into a list of single-word units called tokens). The tokenizer function used in the study is based on the example given in (Sivarajah, 2020) and strips the text features of any punctuation or unnecessary words such as articles or conjunctions (collectively known as “stopwords” in the NLTK library) prior to tokenization taking place. The tokenizer also lemmatizes each token (puts the token into singular, present-tense form) using the built-in WordNetLemmatizer function from the NLTK library.

```
# Create stopwords list

stops = stopwords.words('english')
stops.remove('no')
stops += ['amp', 'aker']
```

```
# Create tokenizer function

lemmatizer = WordNetLemmatizer()

def tokenize(text):
    # Remove non-alphanumeric characters and normalize case
    text = re.sub(r'[^a-zA-Z0-9]', ' ', text.lower())
    # Tokenize text
    tokens = word_tokenize(text)
    # Lemmatize tokens and remove stop words
    tokens = [lemmatizer.lemmatize(word) for word in tokens if word not
              in stops]
    return tokens

# Create tokens column

def get_tokens(x):
    cpt = tokenize(x.company_profile)
    dt = tokenize(x.description)
    rt = tokenize(x.requirements)
    bt = tokenize(x.benefits)
    return cpt + dt + rt + bt

df['tokens'] = df.apply(lambda x: [get_tokens(x)],
                        axis=1, result_type='expand')
```

Also, a column of bigrams (two-word phrases) was created from the “tokens” column:

```
# Create bigrams column

def get_bigrams(token_list):
    bigram_list = list()
    for i in range(len(token_list)-1):
        bigram = token_list[i] + ' ' + token_list[i+1]
        bigram_list.append(bigram)
    return bigram_list

df['bigrams'] = df.apply(lambda x: [get_bigrams(x.tokens)],
                         axis=1, result_type='expand')
```

The tokens and bigrams for fraudulent and legitimate job advertisements were then sorted into separate lists for frequency analysis:

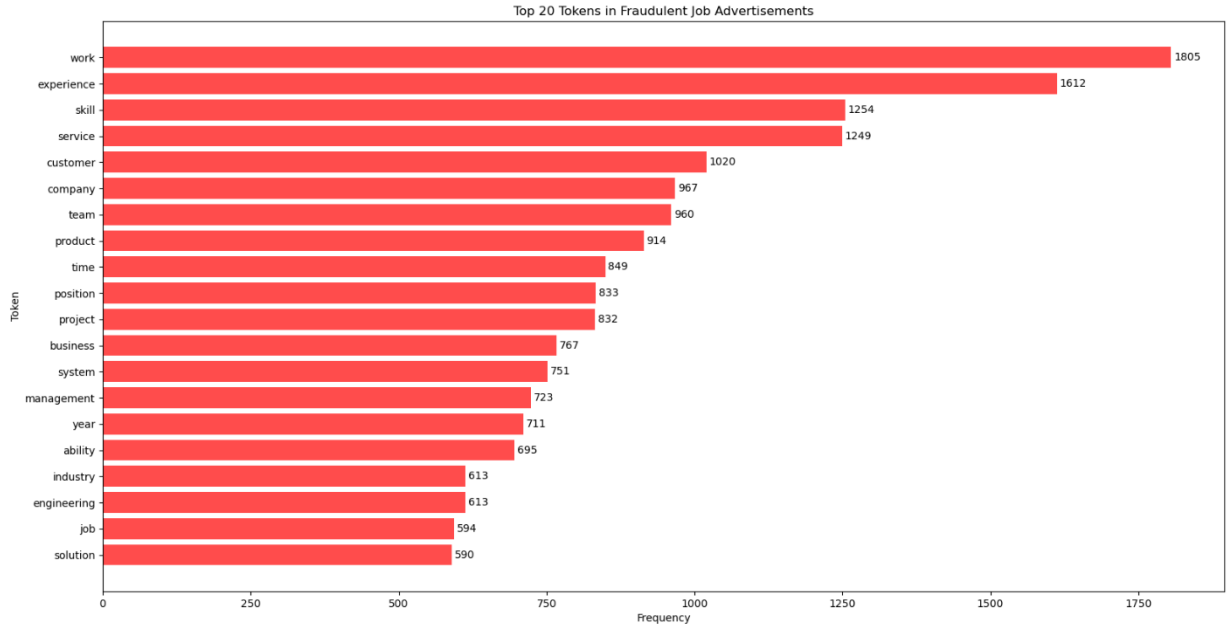
```
# Create lists of tokens & bigrams from fraudulent/legitimate job ads

fraud_tokens, legit_tokens = list(), list()
fraud_bigrams, legit_bigrams = list(), list()
```

```
for i in range(len(df)):
    tok = df.tokens[i]
    bi = df.bigrams[i]
    if df.fraudulent[i] == 1:
        fraud_tokens += tok
        fraud_bigrams += bi
    else:
        legit_tokens += tok
        legit_bigrams += bi
```

A frequency plot of the top 20 tokens in fraudulent job advertisements was generated using the NLTK FreqDist function discussed in Chapter 1 of (Bird et al., 2009):

```
# Top 20 tokens in fraudulent job ads plot

ft_dist = FreqDist(fraud_tokens).most_common(20)
top_ft, ft_freq = list(), list()
for i in range(20):
    top_ft.append(ft_dist[-(i+1)][0])
    ft_freq.append(ft_dist[-(i+1)][1])
plt.barh(top_ft, ft_freq, color='red', alpha=.7)
plt.title('Top 20 Tokens in Fraudulent Job Advertisements')
plt.ylabel('Token')
plt.xlabel('Frequency')
for i in range(20):
    plt.text(ft_freq[i] + 5, i, ft_freq[i], color='black',
             ha='left', va='center')
plt.show()
```

Figure 1: Top 20 tokens in fraudulent job advertisements.



Similar code was used to generate frequency plots of the top 20 tokens in legitimate job advertisements as well as the top 20 bigrams in fraudulent and legitimate job advertisements. These plots are shown in Figures 2-4.

Figure 2: Top 20 tokens in legitimate job advertisements.

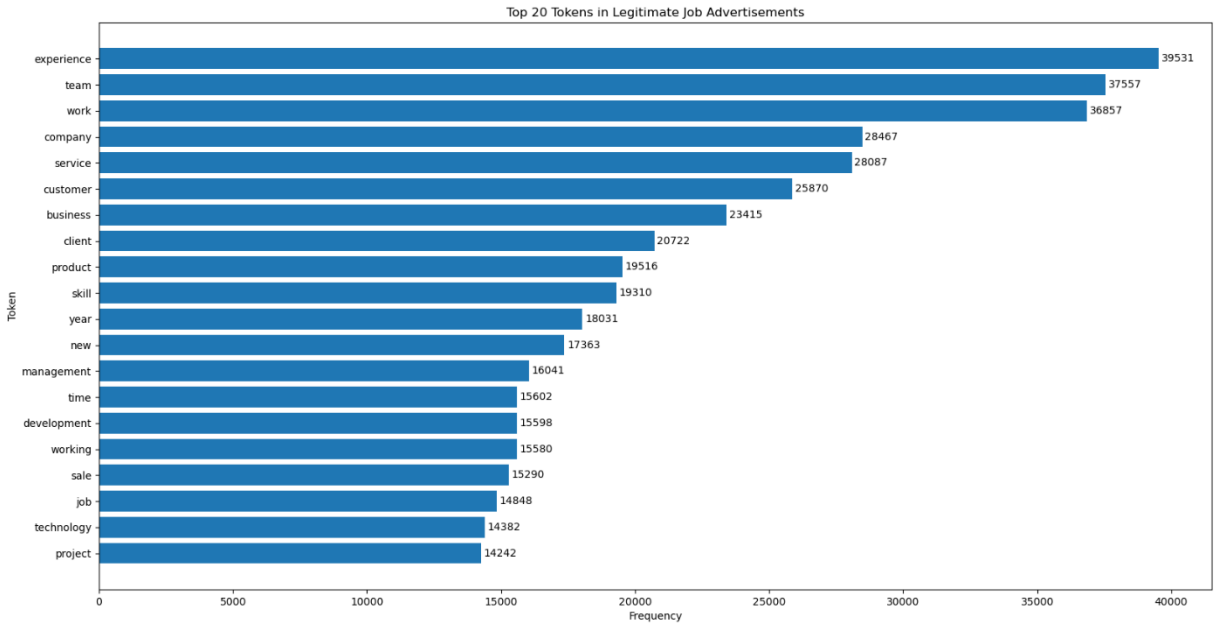


Figure 3: Top 20 bigrams in fraudulent job advertisements.

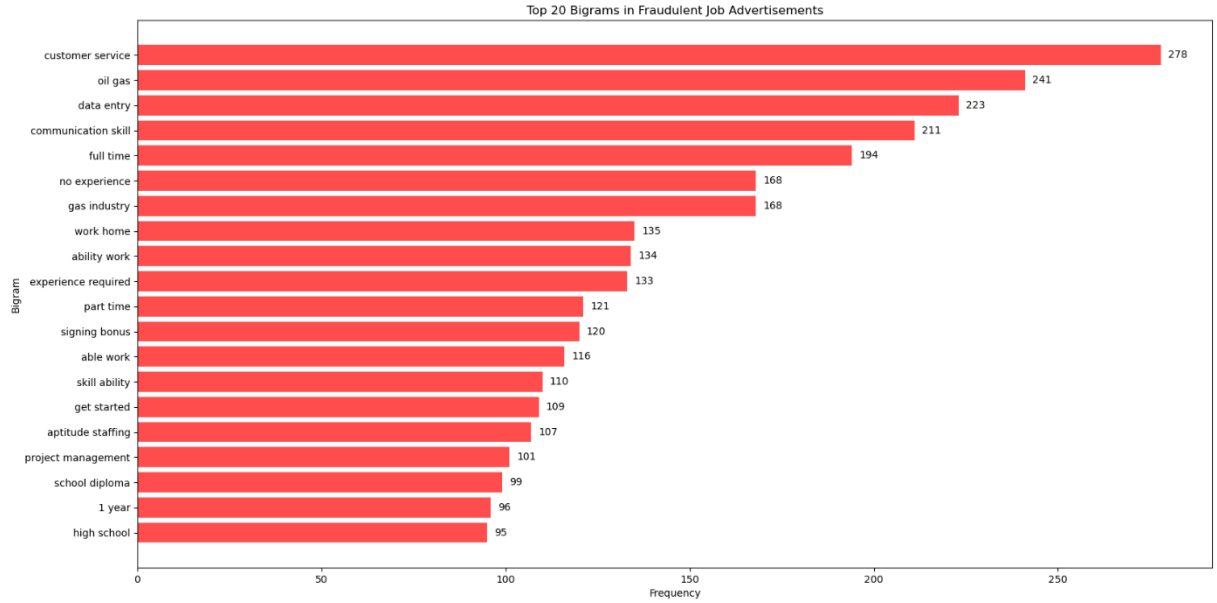
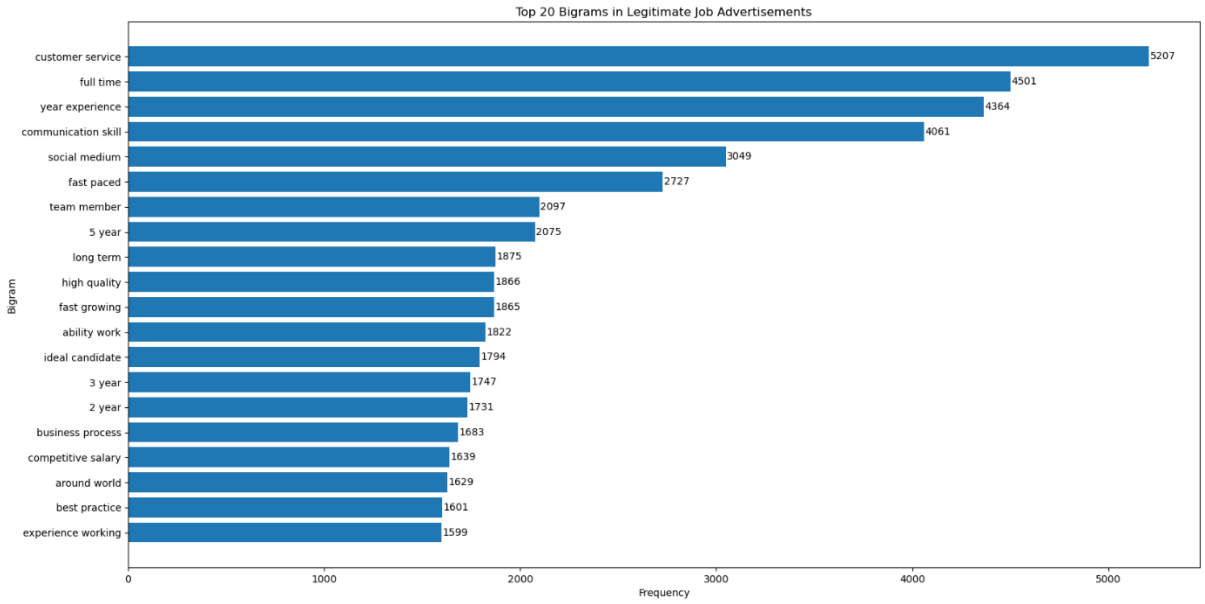


Figure 4: Top 20 bigrams in legitimate job advertisements.



There are some interesting observations to make about Figures 1-4. The fraudulent job advertisements in the EMSCAD do not appear to be significantly different from the legitimate job advertisements in terms of single-word tokens. In Figures 1 and 2, we can see that words such as “work”, “experience”, “skill”, “customer”, and “company” are frequently found in both types of advertisements.

However, the fraudulent job advertisements are noticeably different from the legitimate job advertisements when it comes to bigrams. According to Figure 3, fraudulent job advertisements often contain bigrams such as “data entry”, “no experience”, “work home”, “part time”, “signing bonus”, “get started”, and “high school” which do not appear in Figure 4, the frequency plot for the top 20 bigrams in legitimate job advertisements. These bigrams imply that many of the fraudulent job advertisements in the EMSCAD are work-from-home positions requiring little to no experience and offering signing bonuses to lure applicants. Conversely, the bigrams “fast paced”, “team member”, “5 year”, “long term”, “high quality”, “fast growing”, and

“competitive salary” are unique to legitimate job advertisements. These bigrams indicate that legitimate job advertisements are looking for applicants with long-term commitment and collaboration skills required for positions at actual companies.

Since the presence of certain bigrams may be an effective way of differentiating between fraudulent and legitimate job advertisements, a new binary variable called *has_fraud_bigram* was created which is true if the job advertisement contains a bigram from the “common_fb” list shown below:

```
# Fraudulent bigram indicator

common_fb = ['data entry', 'oil gas', 'gas industry', 'no experience',
             'experience required', 'work home', 'part time', 'signing
             bonus', 'get started', 'high school', 'school diploma']

def has_fb(bigram_list):
    if any([bigram in common_fb for bigram in bigram_list]):
        return 1
    else:
        return 0

df['has_fraud_bigram'] = df.apply(lambda x: [has_fb(x.bigrams)],
                                  axis=1, result_type='expand')
```

Similarly, a new binary variable called *has_legit_bigram* was created which is true if the job advertisement contains a bigram from the “common_lb” list shown below:

```
# Legitimate bigram indicator

common_lb = ['full time', '5 year', '3 year', '2 year', 'long term',
             'team member', 'high quality', 'fast growing', 'fast
             paced', 'ideal candidate', 'competitive salary']

def has_lb(bigram_list):
    if any([bigram in common_lb for bigram in bigram_list]):
        return 1
    else:
        return 0

df['has_legit_bigram'] = df.apply(lambda x: [has_lb(x.bigrams)],
                                  axis=1, result_type='expand')
```

In addition to tokens and bigrams, the presence of email addresses, phone numbers, or links to external websites in a job advertisement could be significant predictors of fraudulent status in the logistic regression model. Hence, the binary variables *has_email*, *has_phone*, and *has_url* were created which are true if any of the job advertisement's four text features (*company_profile*, *description*, *requirements*, *benefits*) contain an email address, phone number, or URL, respectively. The detection of these attributes was made possible by the fact that the creators of the EMSCAD masked email addresses, phone numbers and URLs with the strings "#EMAIL", "#PHONE", and "#URL", respectively.

```
# Merge text features function

def merge_text(x):
    cp = x.company_profile
    d = x.description
    r = x.requirements
    b = x.benefits
    return cp + d + r + b

# Email indicator

def email(text):
    if '#EMAIL' in text:
        return 1
    else:
        return 0

df['has_email'] = df.apply(lambda x: [email(merge_text(x))],
                           axis=1, result_type='expand')
# Phone number indicator

def phone(text):
    if '#PHONE' in text:
        return 1
    else:
        return 0

df['has_phone'] = df.apply(lambda x: [phone(merge_text(x))],
                           axis=1, result_type='expand')
```

```
# External URL indicator

def url(text):
    if '#URL' in text:
        return 1
    else:
        return 0

df['has_url'] = df.apply(lambda x: [url(merge_text(x))],
                         axis=1, result_type='expand')
```

Also, a binary variable called *money_in_title* was created which is true if the character variable *title* contains a "$" symbol. Past studies have shown that fraudulent job advertisements frequently mention salaries or wages in the title to lure applicants (Vidros et al., 2017), so the variable *money_in_title* has the potential to be a strong predictor of fraudulent status in the logistic regression model.

```
# Money in title indicator

def money_in_title(text):
    if '$' in text:
        return 1
    else:
        return 0

df['money_in_title'] = df.apply(lambda x: [money_in_title(x.title)],
                                axis=1, result_type='expand')
```

Finally, for each job advertisement, the number of words in the text features *company_profile*, *description*, *requirements*, and *benefits* were calculated and stored as the variables *company_profile_length*, *description_length*, *requirements_length*, and *benefits_length*.

```
# Word count function

def word_count(text):
    # Remove non-alphanumeric characters
    text = re.sub(r'[^a-zA-Z0-9]', ' ', text)
    return len(text.split())
```

```
df['company_profile_length'] = df.apply(
     lambda x: [word_count(x.company_profile)],
     axis=1, result_type='expand')

df['description_length'] = df.apply(
     lambda x: [word_count(x.description)],
     axis=1, result_type='expand')

df['requirements_length'] = df.apply(
     lambda x: [word_count(x.requirements)],
     axis=1, result_type='expand')

df['benefits_length'] = df.apply(
     lambda x: [word_count(x.benefits)],
     axis=1, result_type='expand')
```

Once all of the new numeric variables had been created, any old variables that were no longer relevant were dropped from the dataset. The text mining results were saved as a CSV file so that they could be imported in SAS Studio.

```
# Drop columns that are no longer needed

df.drop(['title', 'company_profile', 'description', 'requirements',
         'benefits', 'tokens', 'bigrams', 'fraudulent'],
         inplace=True, axis=1)

# Export text mining results as CSV file

df.to_csv(path + '/text_mining_results.csv', index=False)
```

List of New Variables

Back in SAS Studio, the Python text mining results were imported and merged with the "EMSCAD_clean_SWOE" dataset using the following code:

```
/* Import text mining results */

proc import datafile="&path/text_mining_results.csv"
            dbms=csv
            out=capstone.text_mining_results;
      guessingrows=max;
run;
```

```
/* Merge EMSCAD_clean_SWOE and text_mining_results */

%let final_vars=employment_type, required_experience, required_education,
                company_profile_length, description_length,
                requirements_length, benefits_length, industry_SWOE,
                function_SWOE, from_US, money_in_title, mentions_salary,
                telecommuting, has_company_logo, has_questions, has_email,
                has_phone, has_url, has_fraud_bigram, has_legit_bigram,
                fraudulent;
proc sql;
       create table capstone.EMSCAD_final as
              select &final_vars
              from capstone.EMSCAD_clean_SWOE E
              join capstone.text_mining_results T
              on E.job_id=T.job_id;
quit;
```

The resulting "EMSCAD_final" dataset contains the following variables:

Table 8: List of variables in the "EMSCAD_final" dataset.

Variable Name	Type	Description
employment_type	Categorical (6 levels)	Employment type. (Ex: Full-time, part-time, etc.)
required_experience	Categorical (8 levels)	Prior experience required for job. (Ex: Entry level, executive, etc.)
required_education	Categorical (10 levels)	Education level required for job. (Ex: Bachelor's Degree, Master's Degree, etc.)
company_profile_length	Numeric, discrete	Number of words in *company_profile*.
description_length	Numeric, discrete	Number of words in *description*.
requirements_length	Numeric, discrete	Number of words in *requirements*.
benefits_length	Numeric, discrete	Number of words in *benefits*.
industry_SWOE	Numeric, continuous	Smooth weight-of-evidence technique applied to *industry*.
function_SWOE	Numeric, continuous	Smooth weight-of-evidence technique applied to *function*.
from_US	Numeric, binary	True if job advertisement is from the United States.
money_in_title	Numeric, binary	True if *title* contains "$" symbol.
mentions_salary	Numeric, binary	True if job advertisement mentions salary.
telecommuting	Numeric, binary	True for telecommuting/work-from-home positions.

has_company_logo	Numeric, binary	True if company logo is visible in job advertisement.
has_questions	Numeric, binary	True if job advertisement has screening questions.
has_email	Numeric, binary	True if job advertisement contains email address.
has_phone	Numeric, binary	True if job advertisement contains phone number.
has_url	Numeric, binary	True if job advertisement contains link to external website.
has_fraud_bigram	Numeric, binary	True if job advertisement contains a bigram commonly found in fraudulent job advertisements (see pg. 25).
has_legit_bigram	Numeric, binary	True if job advertisement contains a bigram commonly found in legitimate job advertisements (see pg. 25).
fraudulent	Numeric, binary	True if job advertisement is fraudulent.

The first 20 independent variables (*employment_type*, *required_experience*, *required_education*, *company_profile_length*, *description_length*, *requirements_length*, *benefits_length*, *industry_SWOE*, *function_SWOE*, *from_US*, *money_in_title*, *mentions_salary*, *telecommuting*, *has_company_logo*, *has_questions*, *has_email*, *has_phone*, *has_url*, *has_fraud_bigram*, *has_legit_bigram*) have now been thoroughly prepared and can all be used directly to predict the value of *fraudulent*, the binary dependent variable for the logistic regression model.

ANALYSIS

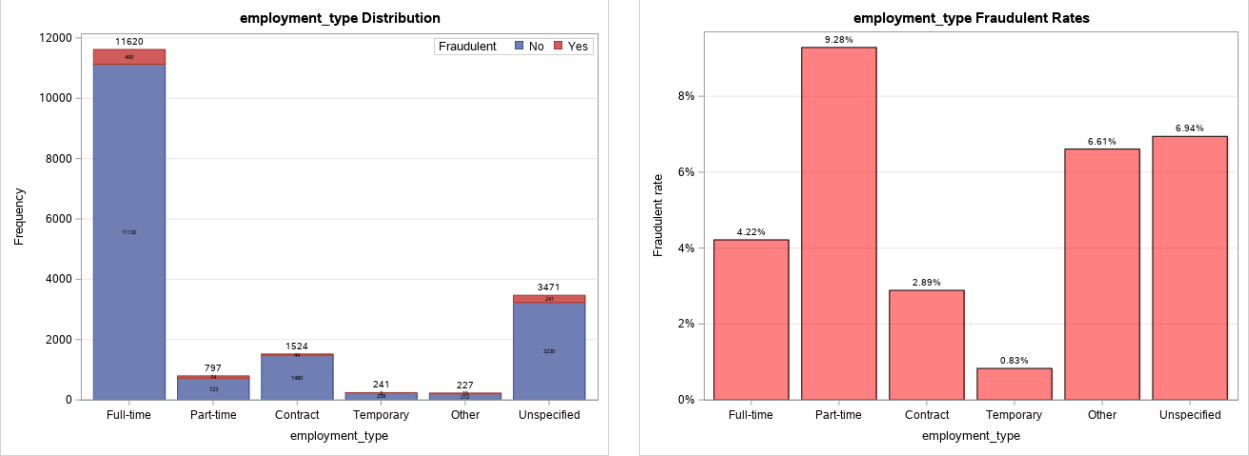
Visualizations

In SAS Studio, the first type of analysis performed on the EMSCAD_final dataset was creating several types of charts and graphs to visualize the distribution of fraudulent job advertisements across the independent variables. These charts and graphs provide many useful insights into the distinguishing features of fraudulent job advertisements. First, the following code was used to create a stacked bar chart showing the distribution of *employment_type* categories grouped by fraudulent status along with a regular bar chart showing the fraudulent rates within each *employment_type* category.

```
/* Create Yes/No format for binary variables */

proc format;
	value yn 1='Yes' 0='No';
run;

/* employment_type distribution */

title 'employment_type Distribution';
proc sgplot data=capstone.EMSCAD_final;
	format fraudulent yn.;
	vbar employment_type / group=fraudulent groupdisplay=stack
	                       datalabel seglabel seglabelattrs=(size=4)
	                       seglabelfitpolicy=noclip;
	xaxis discreteorder=data;
	yaxis label='Frequency' grid;
	keylegend / title='Fraudulent' location=inside position=topright;
run;

/* employment_type fraudulent rates */

proc freq data=capstone.EMSCAD_final noprint;
	tables employment_type*fraudulent / out=FreqOut(where=(fraudulent=1))
	                                    outpct;
run;

data FreqOut;
	set FreqOut;
	row_proportion=PCT_ROW/100;
	keep employment_type row_proportion;
run;
```

```
title 'employment_type Fraudulent Rates';
proc sgplot data=FreqOut;
      format row_proportion percent6.2;
      vbar employment_type / response=row_proportion datalabel
                             fillattrs=(color=red transparency=0.5);
      xaxis discreteorder=data;
      yaxis label='Fraudulent rate' grid;
run;
```

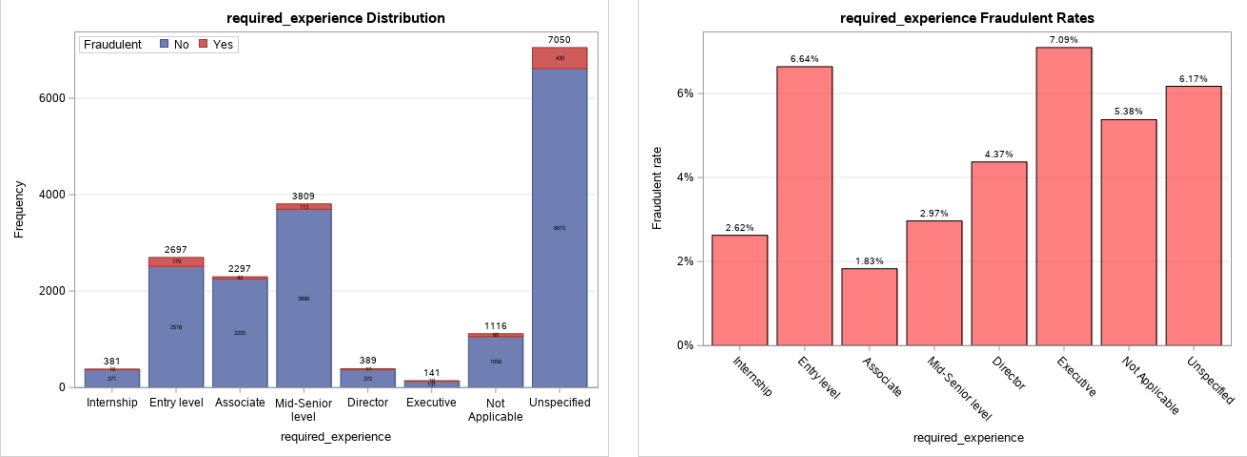
Figure 5: *employment_type* distribution and fraudulent rates.



According to Figure 5, a majority of the job advertisements in the EMSCAD_final dataset (11,620 advertisements representing 64.99% of the data) are full-time positions. Full-time positions also have 490 fraudulent cases which is more than any other employment type. However, looking at the fraudulent rates within each *employment_type* category, "Part-time" has the highest fraudulent rate (9.28%) followed by "Unspecified" in second place (6.94%) and "Other" in third place (6.61%). Therefore, we can conclude that even though full-time positions are the most common and have the most fraudulent cases by sheer numbers, jobs where the commitment level is low ("Part-time", "Other", or "Unspecified") are the riskiest in terms of scam likelihood.

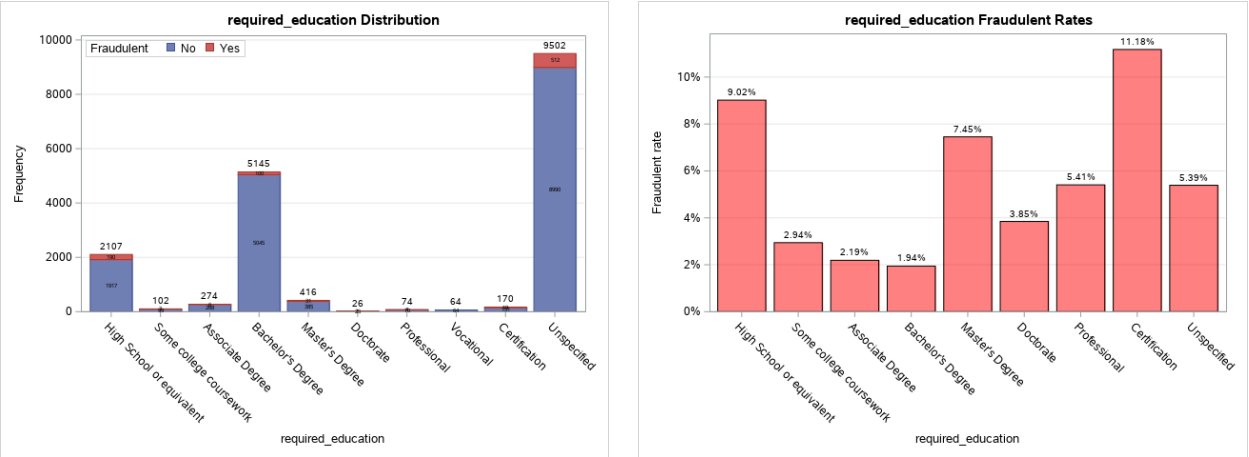
Similar code was used to generate distribution and fraudulent rate plots for the other two categorical variables, *required_experience* and *required_education* (Figures 6 & 7).

Figure 6: *required_experience* distribution and fraudulent rates.



According to Figure 6, the "Unspecified" category where required experience was left blank occurs 7,050 times representing 39.43% of the data, making it the most common required experience level in the EMSCAD_final dataset. The "Unspecified" category also has 435 fraudulent cases which is more than any other *required_experience* category. As for fraudulent rates, the "Executive" category has the highest fraudulent rate (7.09%) followed by "Entry level" in second place (6.64%) and "Unspecified" in third place (6.17%). Thus, it appears that job advertisements where required experience is either very high (the "Executive" level) or very low ("Unspecified" or "Entry level") are more likely to be scams than job advertisements with moderate required experience levels ("Associate" or "Mid-Senior level").

Figure 7: *required_education* distribution and fraudulent rates.



In Figure 7, the *required_education* distribution shows that the "Unspecified" category where required education was left blank occurs 9,502 times representing a majority (53.14%) of the EMSCAD_final dataset, followed by "Bachelor's Degree" in second place (5,145 occurrences) and "High School or equivalent" in third place (2,107 occurrences). The remaining seven categories combined occur 1,126 times and only represent 6.30% of the data. The "Unspecified" category also has the most scams (512). However, looking at the *required_education* fraudulent rates, the "Certification" category has the highest fraudulent rate (11.18%) followed by "High School or equivalent" (9.02%). These results are logical: a job advertisement scam is unlikely to ask for candidates with high education levels because that would deter certain groups of people from applying, and scammers want to reach as wide of an audience as possible in order to maximize their chances of success.

Next, the four text feature length variables *company_profile_length*, *description_length*, *requirements_length*, and *benefits_length* were analyzed with histograms and box plots (Figures 8-11). The code shown below was used to create the *company_profile_length* histogram and box plot; the histograms and box plots for the other three variables were generated in a similar fashion. The SAS article (Matange, 2015) was referenced for the box plot code.

```
/* company_profile_length histogram */

title 'company_profile_length Histogram';
proc sgplot data=capstone.EMSCAD_final;
	histogram company_profile_length / scale=count;
	yaxis label='Frequency' grid;
run;

/* company_profile_length box plot */

options validvarname=v7;
ods output sgplot=cpl_boxplotdata(rename=(
	BOX_COMPANY_PROFILE_LENGTH_X___Y=value
	BOX_COMPANY_PROFILE_LENGTH_X__ST=stat
	BOX_COMPANY_PROFILE_LENGTH_X___X=cat));
proc sgplot data=capstone.EMSCAD_final;
	vbox company_profile_length / category=fraudulent;
run;

data cpl_merged;
	format fraudulent cat yn.;
	set capstone.EMSCAD_final
	    cpl_boxplotdata(where=(value ne . and
	        stat in ('MIN' 'Q1' 'MEDIAN' 'Q3' 'MAX' 'MEAN')));
	value=round(value, 0.01);
	run;

title 'company_profile_length Box Plot';
proc sgplot data=cpl_merged noautolegend;
	vbox company_profile_length / category=fraudulent group=fraudulent
	                              fillattrs=(transparency=0.7)
	                              meanattrs=(symbol=diamond);
	xaxistable value / x=cat class=stat location=inside;
	yaxis grid;
run;
```

Figure 8: *company_profile_length* histogram and box plot.

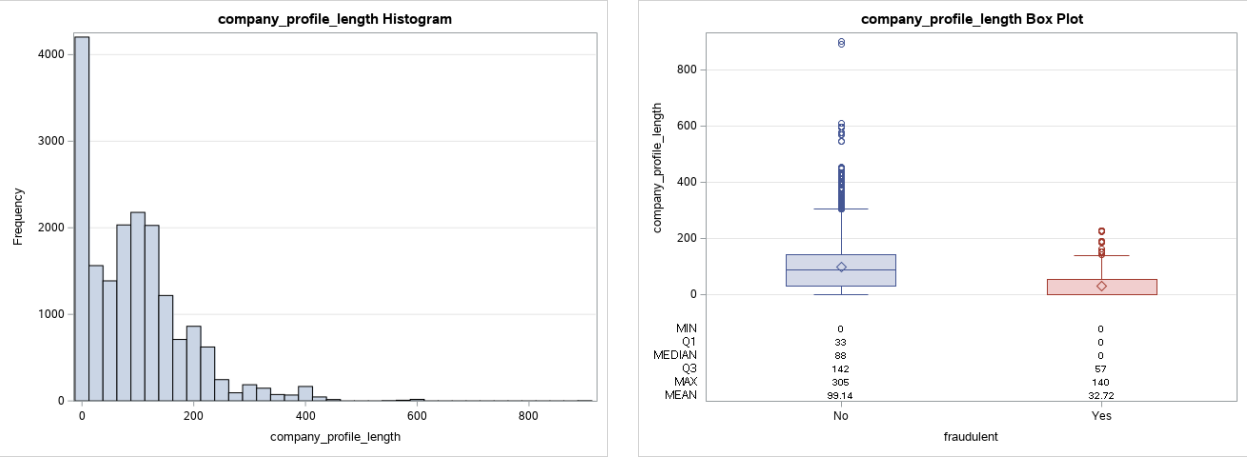


Figure 9: *description_length* histogram and box plot.

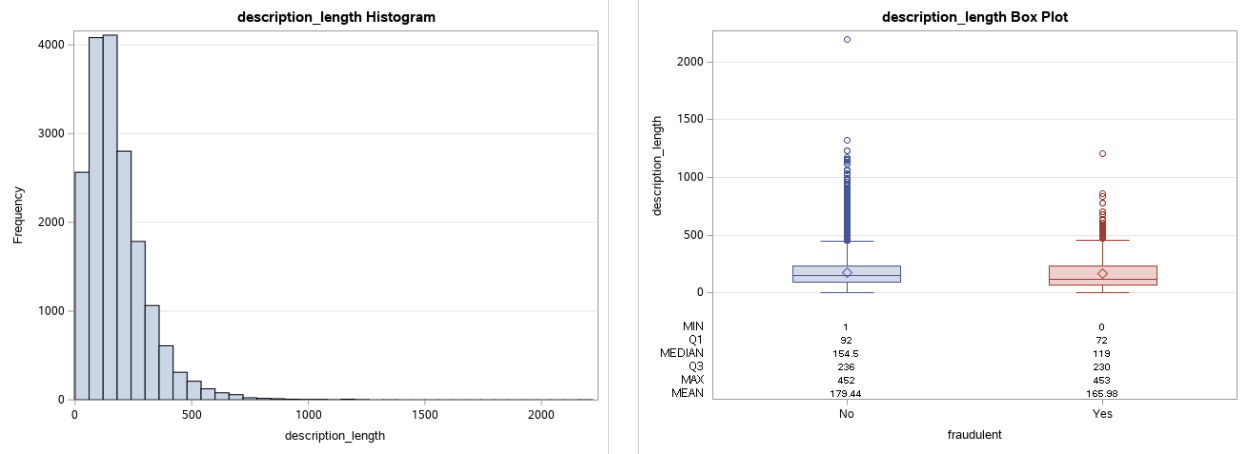


Figure 10: *requirements_length* histogram and box plot.

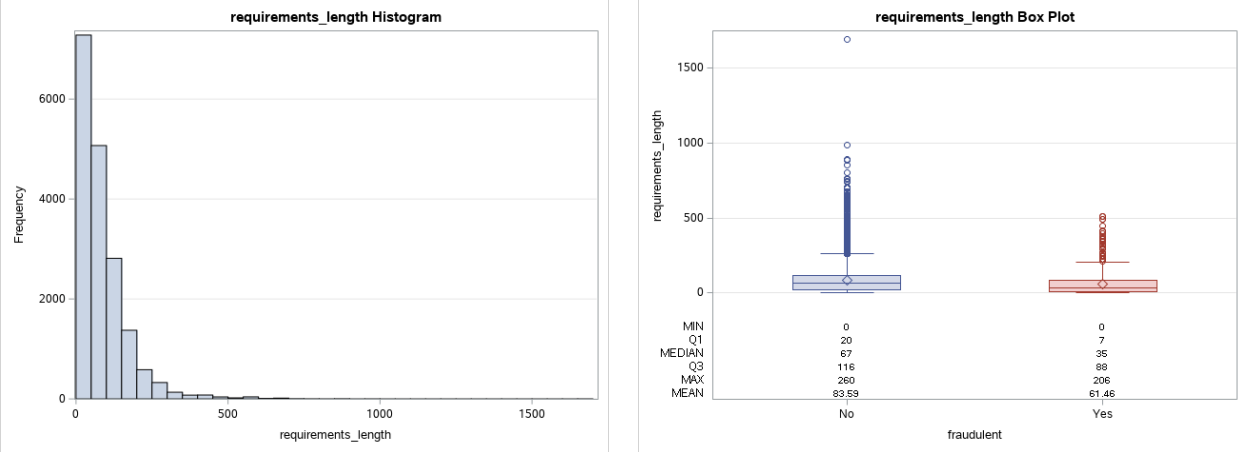
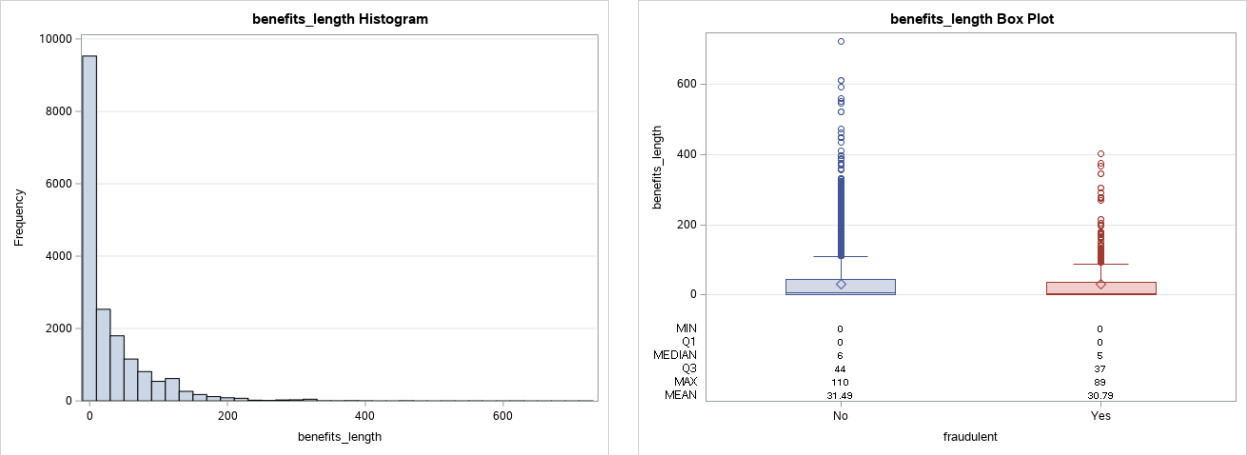


Figure 11: *benefits_length* histogram and box plot.



Looking at the histograms in Figures 8-11, the distributions of *company_profile_length*, *description_length*, *requirements_length* and *benefits_length* are all skewed to the right which means that there are more job advertisements in the EMSCAD_final dataset with short or blank text features than there are job advertisements with long, detailed text features. In addition, the box plots in Figures 8-11 indicate that fraudulent job advertisements are consistently shorter than legitimate job advertisements across all four text features. In particular, legitimate job advertisements have a mean company profile length of 99.14 words while fraudulent job advertisements have a mean company profile length of 32.72 words; legitimate job advertisements have a mean description length of 179.44 words while fraudulent job advertisements have a mean description length of 165.98 words; legitimate job advertisements have a mean requirements length of 83.59 words while fraudulent job advertisements have a mean requirements length of 61.46 words; and last but not least, legitimate job advertisements have a mean benefits length of 31.49 words while fraudulent job advertisements have a mean benefits length of 30.79 words. Clearly, shorter job advertisements are more likely to be scams than longer job advertisements.

Finally, the distributions and fraudulent rates of the binary variables in the EMSCAD_final dataset were visualized with the same code that was used for the categorical variable plots in Figures 5-7. The binary variable plots are shown in Figures 12-22.

Figure 12: *from_US* distribution and fraudulent rates.

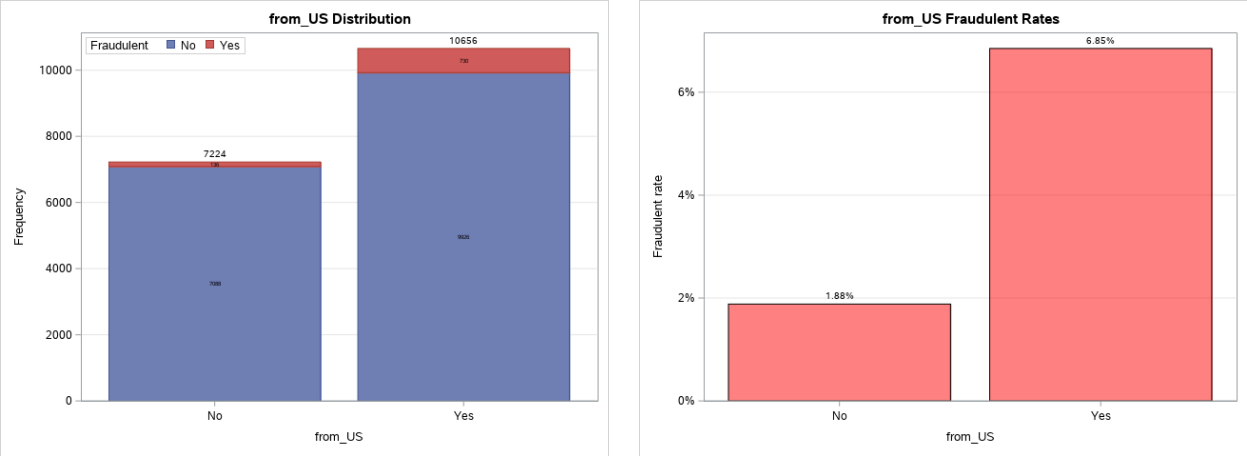


Figure 13: *money_in_title* distribution and fraudulent rates.

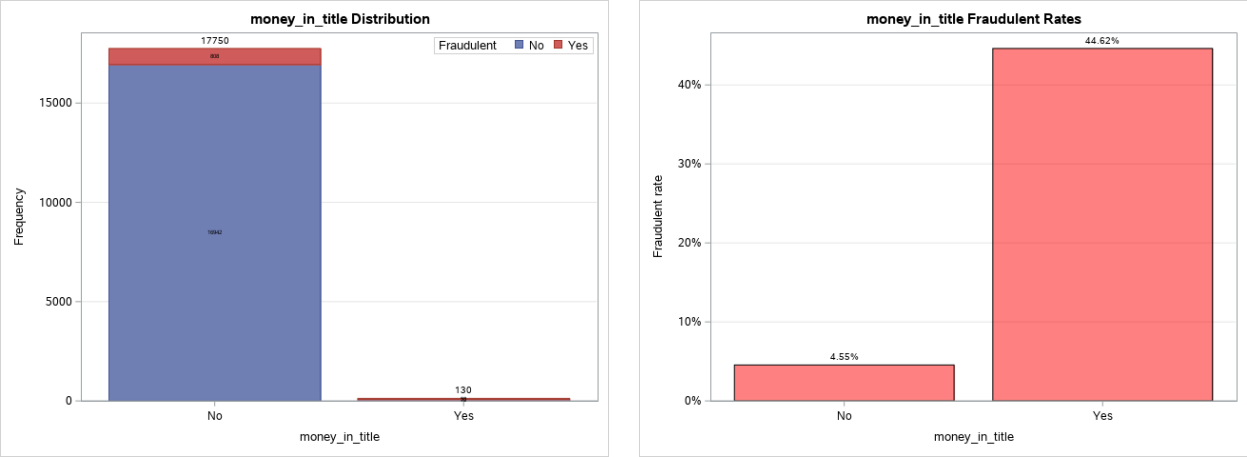
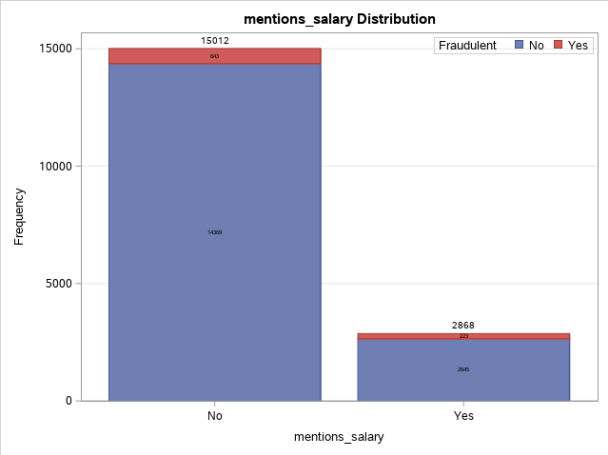


Figure 14: *mentions_salary* distribution and fraudulent rates.



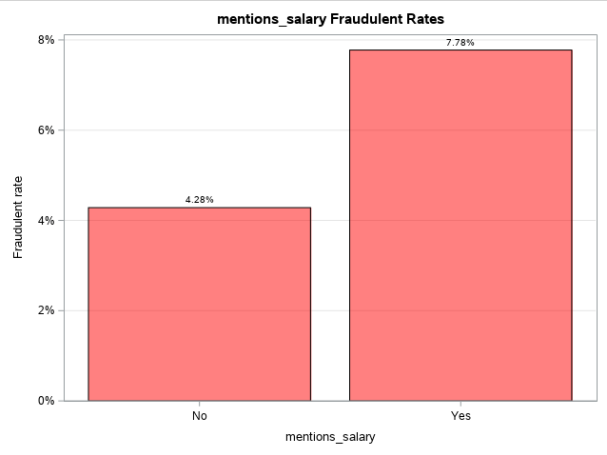
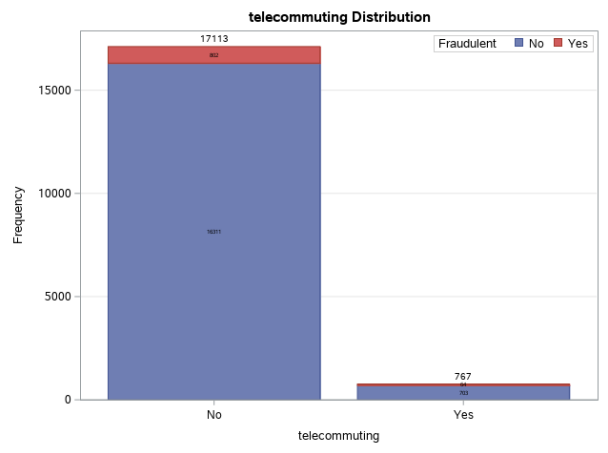


Figure 15: *telecommuting* distribution and fraudulent rates.



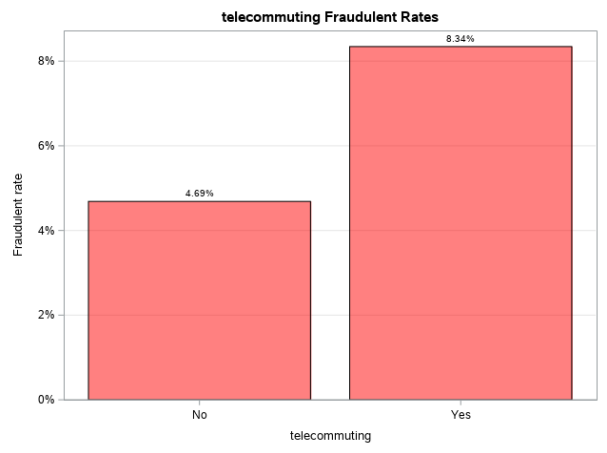
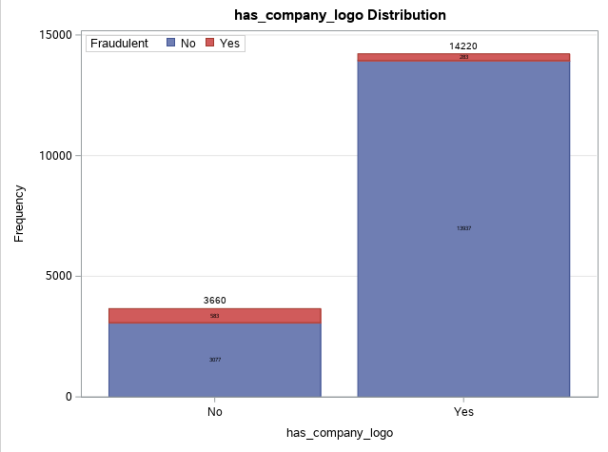


Figure 16: *has_company_logo* distribution and fraudulent rates.



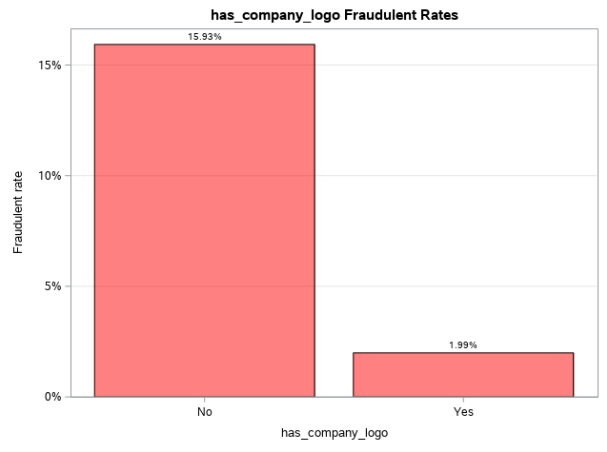
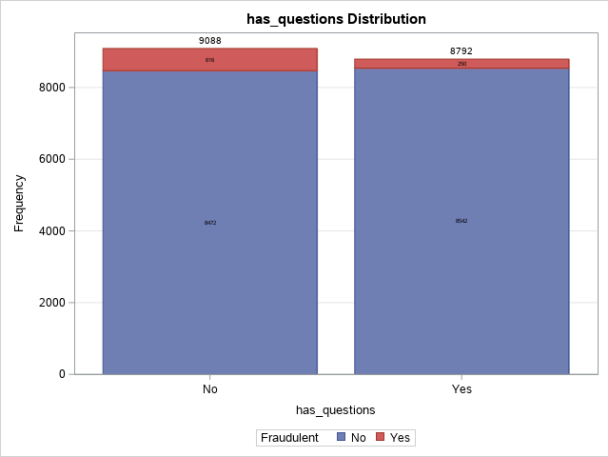


Figure 17: *has_questions* distribution and fraudulent rates.



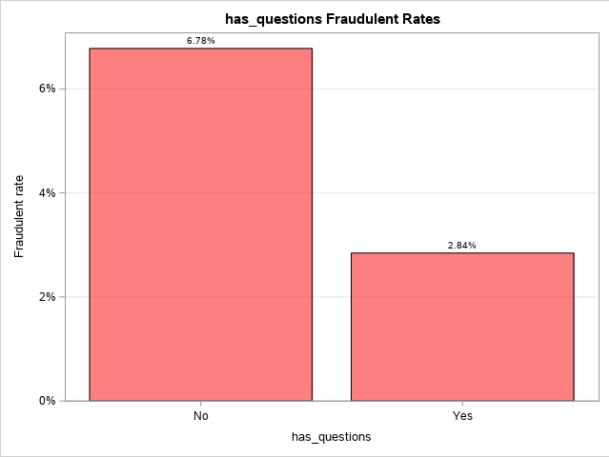
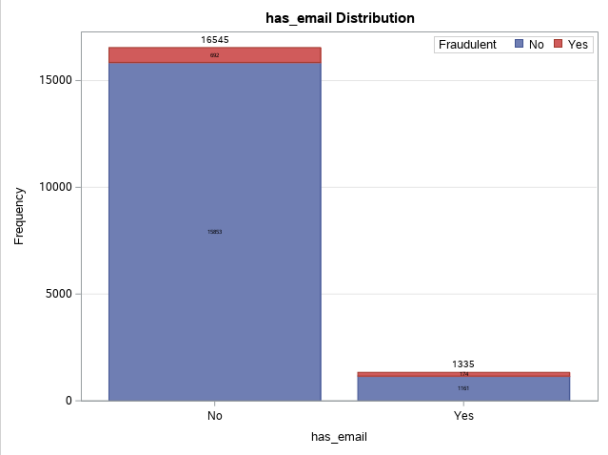


Figure 18: *has_email* distribution and fraudulent rates.



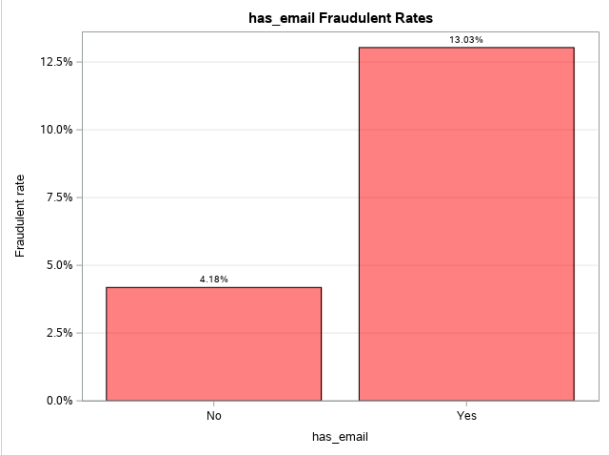
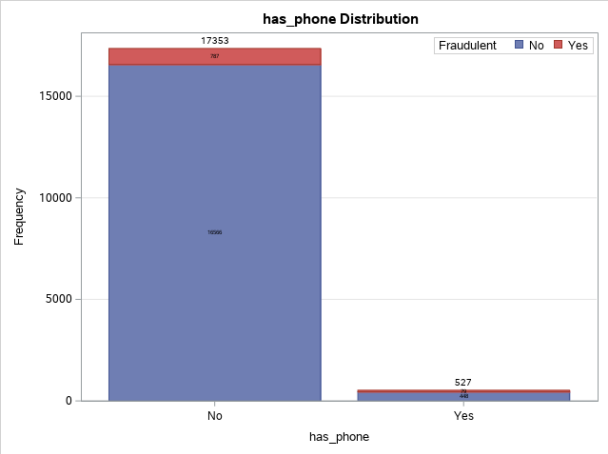


Figure 19: *has_phone* distribution and fraudulent rates.



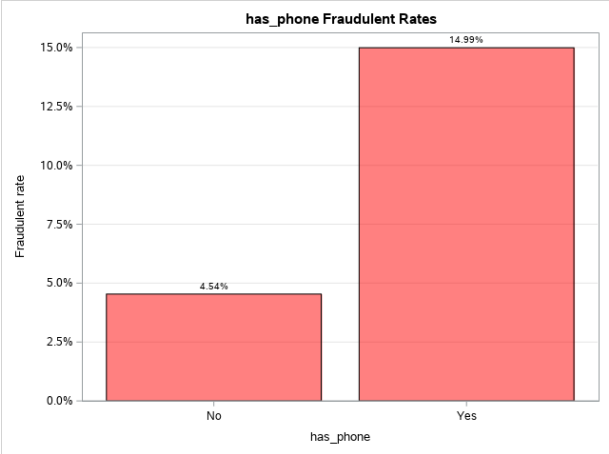
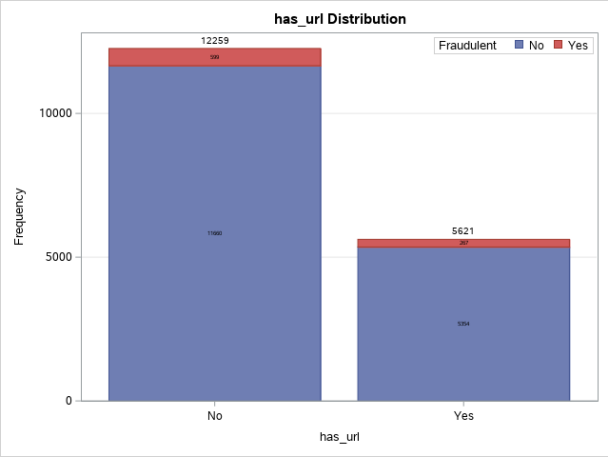


Figure 20: *has_url* distribution and fraudulent rates.



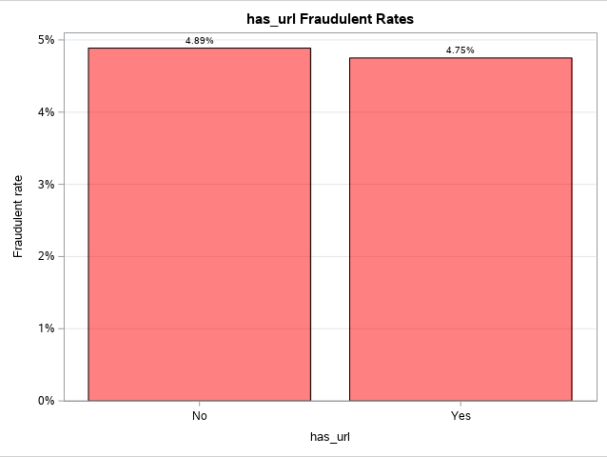
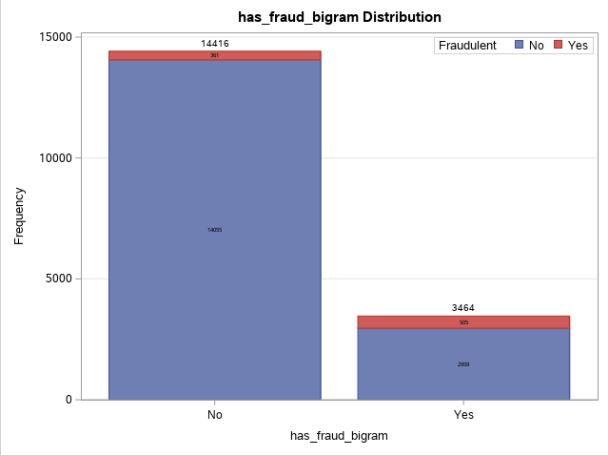


Figure 21: *has_fraud_bigram* distribution and fraudulent rates.



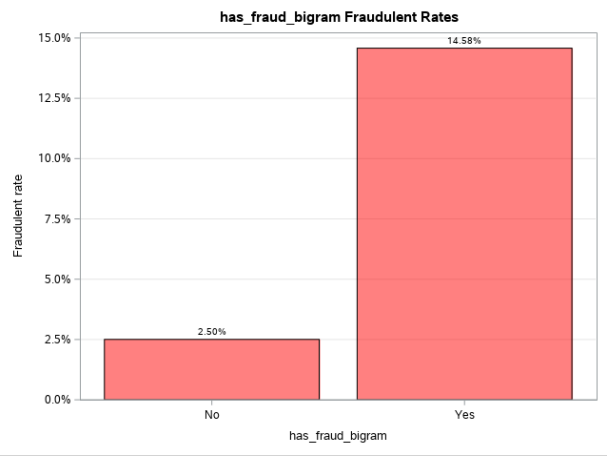
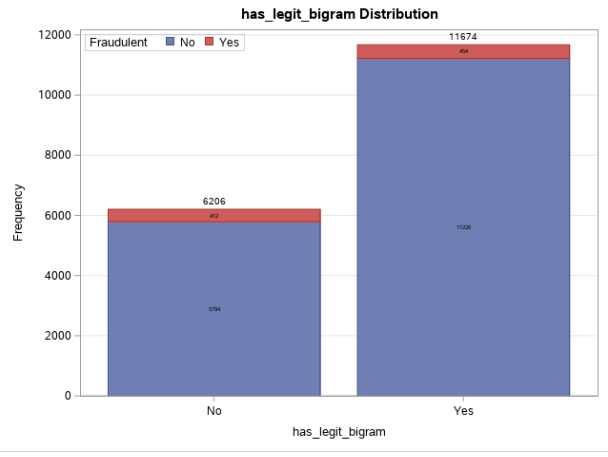
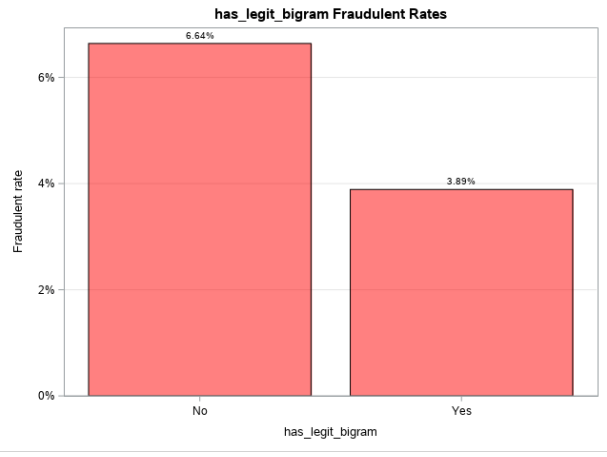


Figure 22: *has_legit_bigram* distribution and fraudulent rates.





Here are several key observations about Figures 12-22:

- According to Figure 13, the vast majority of the job advertisements in the EMSCAD_final dataset (17,750 advertisements representing 99.27% of the data) do not contain a "$" symbol in the title. However, the job advertisements which do have a dollar sign in the title have a fraudulent rate of 44.62% which is the highest fraudulent rate of any independent variable that has been examined so far. Hence, even though job advertisements which mention money in the title are rare, when they do occur, there is a high probability that the advertisement is a scam.
- Looking at Figures 12, 14, 15, 18, and 19, when a job advertisement comes from the United States, mentions salary, supports telecommuting, or contains an email address or phone number, the probability that the advertisement is a scam increases. On the other hand, from Figures 16 and 17, when a job advertisement has a company logo or screening questions, the probability that the advertisement is a scam decreases.
- In Figure 20, the presence of a link to an external website does not appear to have a significant effect on fraudulent status. The fraudulent rate of job advertisements which do not have URLs (4.89%) is roughly the same as the fraudulent rate of job advertisements which do have URLs (4.75%).
- According to Figure 21, job advertisements which contain a common fraud bigram have a higher fraudulent rate (14.58%) than job advertisements which do not (2.50%). This is a good sign that the *has_fraud_bigram* variable is meaningful. Likewise, in Figure 22, job advertisements which contain a common legitimate bigram have a lower fraudulent rate (3.89%) than job advertisements which do not (6.64%). Hence, *has_legit_bigram* may also be a good predictor of fraudulent status in the logistic regression model.

Training and Validation Datasets

A standard practice for creating a logistic regression model (and most predictive models for that matter) is to split the data into training and validation datasets. The training dataset is used to form various candidate models while the validation dataset is used for model comparison and selecting the best model. However, when the target event is rare in the initial dataset, it may be necessary to oversample observations with the target event prior to forming the training and validation datasets (Patetta, Lesson 1.2). This is certainly the case with the EMSCAD_final dataset where fraudulent job advertisements only make up 4.84% of the data. The predicted probabilities of the logistic regression model will then need to be adjusted for oversampling later on. Here is the code that was used to oversample the EMSCAD_final dataset:

```
/* Sort EMSCAD_final by fraudulent */

proc sort data=capstone.EMSCAD_final;
      by fraudulent;
run;

/* Oversample fraudulent cases to form development dataset */

proc surveyselect data=capstone.EMSCAD_final
                  method=srs n=(2598, 866) seed=6302021
                  out=capstone.development(drop=SelectionProb SamplingWeight);
      strata fraudulent;
run;
```

The development dataset contains all 866 fraudulent job advertisements and 2,598 randomly selected legitimate job advertisements from the EMSCAD_final dataset so that fraudulent advertisements now make up 25% of the data, a percentage that should be sufficiently large for logistic regression (Bhalla, 2015). In order to make the results reproducible, the SEED option was enabled to fix the seed of the random number generator used by the SURVEYSELECT procedure to randomly select the legitimate job advertisements. From here, the training and validation datasets were formed with the following code:

```
/* Take stratified sample of development dataset */

proc surveyselect data=capstone.development samprate=0.7
                  seed=6302021 out=capstone.sample outall;
      strata fraudulent;
run;

/* Split sample into training & validation datasets */

data capstone.training(drop=Selected SelectionProb SamplingWeight)
     capstone.validation(drop=Selected SelectionProb SamplingWeight);
      set capstone.sample;
      if selected then output capstone.training;
      else output capstone.validation;
run;
```

In the second SURVEYSELECT procedure, the SAMPRATE=0.7 option randomly assigns 70% of the development dataset to the training dataset and the remaining 30% to the validation dataset. The STRATA statement ensures that the 25% proportion of fraudulent cases is maintained in both the training and validation datasets. Again, the SEED option was turned on to make the data partitioning process reproducible.

All-Variables Model

Now that the training and validation datasets have been formed, we are finally ready to create a logistic regression model to predict whether a job advertisement is fraudulent based on the various advertisement features in the EMSCAD_final dataset (Table 8). To be clear, logistic regression is an appropriate modeling technique because other techniques such as linear regression require the dependent variable to be a continuous numeric variable, whereas *fraudulent* is binary (Patetta, Lesson 2.1). The first logistic regression model that was explored was an all-variables model where all 20 independent variables in the EMSCAD_final dataset were included in the model. Here is the code that was used to create the all-variables model:

```
/* List of all predictors */

%let all_vars=employment_type required_experience required_education
              company_profile_length description_length requirements_length
```

```
                benefits_length industry_SWOE function_SWOE from_US
                money_in_title mentions_salary telecommuting has_company_logo
                has_questions has_email has_phone has_url has_fraud_bigram
                has_legit_bigram;

/* Determine population proportion of fraudulent job ads */

%global rho1;

proc sql;
      select mean(fraudulent) into: rho1
      from capstone.EMSCAD_final;
quit;

/* All-variables model */

proc logistic data=capstone.training;
      class employment_type(ref='Unspecified')
            required_experience(ref='Unspecified')
            required_education(ref='Unspecified') / param=ref;
      model fraudulent(event='1')=&all_vars;
      score data=capstone.validation priorevent=&rho1 fitstat
            out=capstone.validation(rename=(p_1=p_allvars)
                                    drop=F_fraudulent I_fraudulent p_0);
run;
```

In the CLASS statement of the LOGISTIC procedure, the categorical variables *employment_type*, *required_experience*, and *required_education* were encoded using reference cell encoding with the "Unspecified" category serving as the reference level for all three variables. The SCORE statement was used to score the validation dataset, storing the predicted probabilities of the job advertisements being fraudulent as a new column called "p_allvars". The PRIOREVENT option in the SCORE statement adjusts the predicted probabilities for oversampling using $\rho_1 = 4.84\%$, the proportion of fraudulent job advertisements in the initial EMSCAD_final dataset. The FITSTAT option displays various model fit statistics for assessing the predictive power of the all-variables model. The primary outputs of the LOGISTIC procedure for the all-variables model are shown in Tables 9-13.

Table 9: Hypothesis testing (all-variables model).[4]

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	1382.5445	38	<.0001
Score	1070.9115	38	<.0001
Wald	485.4209	38	<.0001

Table 10: Type 3 analysis of effects (all-variables model).

Effect	DF	Wald Chi-Square	Pr > ChiSq
employment_type	5	3.3435	0.6472
required_experience	7	4.8834	0.6742
required_education	9	21.5566	0.0104
company_profile_length	1	28.4588	<.0001
description_length	1	3.9137	0.0479
requirements_length	1	4.2647	0.0389
benefits_length	1	10.4247	0.0012
industry_SWOE	1	113.2490	<.0001
function_SWOE	1	34.1659	<.0001
from_US	1	37.1678	<.0001
money_in_title	1	17.3059	<.0001
mentions_salary	1	31.0755	<.0001
telecommuting	1	0.0480	0.8265
has_company_logo	1	51.4228	<.0001
has_questions	1	1.5341	0.2155
has_email	1	5.8718	0.0154
has_phone	1	6.1146	0.0134
has_url	1	0.7015	0.4023
has_fraud_bigram	1	73.7307	<.0001
has_legit_bigram	1	8.7629	0.0031

[4] The hypotheses being tested are the null hypothesis H_0 and alternative hypothesis H_a from the Hypothesis section (pg. 2). Table 9 indicates that we reject H_0 in favor of H_a at the 5% significance level for all three of the tests shown (Likelihood Ratio, Score, and Wald).

Table 11: Analysis of maximum likelihood estimates (all-variables model).

Parameter	Category	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	3.2745	0.4156	62.0851	<.0001
employment_type	Contract	1	-0.0128	0.3314	0.0015	0.9693
employment_type	Full-time	1	-0.2742	0.2140	1.6417	0.2001
employment_type	Other	1	0.4946	0.6276	0.6209	0.4307
employment_type	Part-time	1	-0.1495	0.3181	0.2210	0.6382
employment_type	Temporary	1	-13.9709	705.3	0.0004	0.9842
required_experience	Associate	1	-0.5587	0.3461	2.6060	0.1065
required_experience	Director	1	0.0618	0.5681	0.0118	0.9134
required_experience	Entry level	1	-0.3128	0.2852	1.2029	0.2727
required_experience	Executive	1	-0.2805	0.6909	0.1648	0.6848
required_experience	Internship	1	-0.3356	0.7791	0.1856	0.6666
required_experience	Mid-Senior level	1	-0.4958	0.2786	3.1666	0.0752
required_experience	Not Applicable	1	-0.1944	0.3303	0.3466	0.5561
required_education	Associate Degree	1	1.1902	0.7970	2.2302	0.1353
required_education	Bachelor’s Degree	1	0.7021	0.2612	7.2274	0.0072
required_education	Certification	1	0.4298	0.6828	0.3962	0.5290
required_education	Doctorate	1	-12.6735	2770.9	0.0000	0.9964
required_education	High School or equivalent	1	0.5531	0.2649	4.3604	0.0368
required_education	Master’s Degree	1	1.9047	0.4856	15.3881	<.0001
required_education	Professional	1	-0.5885	1.4488	0.1650	0.6846
required_education	Some college coursework	1	1.5433	1.0009	2.3772	0.1231
required_education	Vocational	1	-15.1643	1062.9	0.0002	0.9886
company_profile_length		1	-0.00888	0.00166	28.4588	<.0001
description_length		1	-0.00106	0.000535	3.9137	0.0479
requirements_length		1	-0.00190	0.000918	4.2647	0.0389
benefits_length		1	0.00483	0.00150	10.4247	0.0012
industry_SWOE		1	0.8397	0.0789	113.2490	<.0001

function_SWOE		1	0.5868	0.1004	34.1659	<.0001
from_US		1	1.1358	0.1863	37.1678	<.0001
money_in_title		1	2.0637	0.4961	17.3059	<.0001
mentions_salary		1	1.1383	0.2042	31.0755	<.0001
telecommuting		1	0.0662	0.3023	0.0480	0.8265
has_company_logo		1	-1.4743	0.2056	51.4228	<.0001
has_questions		1	-0.2008	0.1621	1.5341	0.2155
has_email		1	0.7775	0.3209	5.8718	0.0154
has_phone		1	0.9291	0.3757	6.1146	0.0134
has_url		1	0.1387	0.1656	0.7015	0.4023
has_fraud_bigram		1	1.3820	0.1609	73.7307	<.0001
has_legit_bigram		1	-0.4379	0.1479	8.7629	0.0031

Table 12: Odds ratio estimates (all-variables model).

Effect	Point Estimate	95% Wald Confidence Limits	
employment_type Contract vs. Unspecified	0.987	0.516	1.890
employment_type Full-time vs. Unspecified	0.760	0.500	1.156
employment_type Other vs. Unspecified	1.640	0.479	5.611
employment_type Part-time vs. Unspecified	0.861	0.462	1.606
employment_type Temporary vs. Unspecified	<0.001	<0.001	>999.999
required_experience Associate vs. Unspecified	0.572	0.290	1.127
required_experience Director vs. Unspecified	1.064	0.349	3.239
required_experience Entry level vs. Unspecified	0.731	0.418	1.279
required_experience Executive vs. Unspecified	0.755	0.195	2.926
required_experience Internship vs. Unspecified	0.715	0.155	3.292
required_experience Mid-Senior level vs. Unspecified	0.609	0.353	1.052
required_experience Not Applicable vs. Unspecified	0.823	0.431	1.573
required_education Associate Degree vs. Unspecified	3.288	0.689	15.678
required_education Bachelor’s Degree vs. Unspecified	2.018	1.210	3.367
required_education Certification vs. Unspecified	1.537	0.403	5.860
required_education Doctorate vs. Unspecified	<0.001	<0.001	>999.999
required_education High School or equivalent vs. Unspecified	1.739	1.035	2.922

required_education Master's Degree vs. Unspecified	6.718	2.594	17.399
required_education Professional vs. Unspecified	0.555	0.032	9.497
required_education Some college coursework vs. Unspecified	4.680	0.658	33.283
required_education Vocational vs. Unspecified	<0.001	<0.001	>999.999
company_profile_length	0.991	0.988	0.994
description_length	0.999	0.998	1.000
requirements_length	0.998	0.996	1.000
benefits_length	1.005	1.002	1.008
industry_SWOE	2.316	1.984	2.703
function_SWOE	1.798	1.477	2.189
from_US	3.114	2.161	4.486
money_in_title	7.875	2.978	20.821
mentions_salary	3.122	2.092	4.658
telecommuting	1.068	0.591	1.932
has_company_logo	0.229	0.153	0.343
has_questions	0.818	0.595	1.124
has_email	2.176	1.160	4.081
has_phone	2.532	1.212	5.288
has_url	1.149	0.830	1.589
has_fraud_bigram	3.983	2.905	5.460
has_legit_bigram	0.645	0.483	0.862

Table 13: Model fit statistics for validation dataset (all-variables model).

Statistic	Value
Log Likelihood	-463.4
Error Rate	0.1753
AIC	1004.811
AICC	1007.937
BIC	1197.668
SC	1197.668
R-Square	0.499674
Max-Rescaled R-Square	0.628419
AUC	0.925456
Brier Score	0.127046

Stepwise Selection Model

The second logistic regression model that was explored was a stepwise selection model where SAS sequentially adds or removes variables from the model until only variables that are statistically significant at a predetermined significance level remain. Here is the code that was used to create the stepwise selection model:

```
/* Stepwise selection model */

proc logistic data=capstone.training;
      class employment_type(ref='Unspecified')
            required_experience(ref='Unspecified')
            required_education(ref='Unspecified') / param=ref;
      model fraudulent(event='1')=&all_vars / selection=stepwise;
      score data=capstone.validation priorevent=&rho1 fitstat
            out=capstone.validation(rename=(p_1=p_stepwise)
                                    drop=F_fraudulent I_fraudulent p_0);
run;
```

The LOGISTIC procedure shown here is similar to the one that was used to create the all-variables model except that the SELECTION=stepwise option was added to the MODEL statement to perform stepwise selection at the default 5% significance level. Again, a SCORE statement was included to score the validation dataset, storing the predicted probabilities of a job advertisement being fraudulent (corrected for oversampling using the PRIOREVENT option) as a new column called "p_stepwise." The primary outputs of the LOGISTIC procedure for the stepwise selection model are shown in Tables 14-18.

Table 14: Summary of stepwise selection.

Step	Effect		DF	Number In	Score Chi-Square	Wald Chi-Square	Pr > ChiSq
	Entered	Removed					
1	has_company_logo		1	1	536.4143		<.0001
2	has_fraud_bigram		1	2	311.4560		<.0001

3	industry_SWOE		1	3	176.7411		<.0001
4	function_SWOE		1	4	42.5643		<.0001
5	has_phone		1	5	32.7014		<.0001
6	company_profile_length		1	6	32.6060		<.0001
7	mentions_salary		1	7	32.7504		<.0001
8	from_US		1	8	33.9760		<.0001
9	money_in_title		1	9	26.8348		<.0001
10	benefits_length		1	10	15.7599		<.0001
11	has_legit_bigram		1	11	14.5310		0.0001
12	required_education		9	12	21.4043		0.0110
13	requirements_length		1	13	6.1172		0.0134
14	has_email		1	14	6.1185		0.0134
15	description_length		1	15	3.9300		0.0474

Table 15: Type 3 analysis of effects (stepwise selection model).

Effect	DF	Wald Chi-Square	Pr > ChiSq
required_education	9	18.6373	0.0285
company_profile_length	1	31.6527	<.0001
description_length	1	3.8814	0.0488
requirements_length	1	5.4356	0.0197
benefits_length	1	9.4155	0.0022
industry_SWOE	1	117.6376	<.0001
function_SWOE	1	37.0939	<.0001
from_US	1	38.5176	<.0001
money_in_title	1	18.8402	<.0001
mentions_salary	1	28.0055	<.0001
has_company_logo	1	59.3067	<.0001

has_email	1	6.0338	0.0140
has_phone	1	5.4669	0.0194
has_fraud_bigram	1	83.9056	<.0001
has_legit_bigram	1	9.9812	0.0016

Table 16: Analysis of maximum likelihood estimates (stepwise selection model).

Parameter	Category	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	3.1268	0.3928	63.3686	<.0001
required_education	Associate Degree	1	0.7135	0.7659	0.8677	0.3516
required_education	Bachelor's Degree	1	0.3599	0.2185	2.7129	0.0995
required_education	Certification	1	0.2138	0.6628	0.1041	0.7470
required_education	Doctorate	1	-11.8825	1693.7	0.0000	0.9944
required_education	High School or equivalent	1	0.2652	0.2143	1.5315	0.2159
required_education	Master's Degree	1	1.6393	0.4162	15.5145	<.0001
required_education	Professional	1	-1.0105	1.3830	0.5338	0.4650
required_education	Some college coursework	1	1.0298	0.9738	1.1184	0.2903
required_education	Vocational	1	-14.2418	661.8	0.0005	0.9828
company_profile_length		1	-0.00929	0.00165	31.6527	<.0001
description_length		1	-0.00103	0.000522	3.8814	0.0488
requirements_length		1	-0.00211	0.000903	5.4356	0.0197
benefits_length		1	0.00442	0.00144	9.4155	0.0022
industry_SWOE		1	0.8364	0.0771	117.6376	<.0001
function_SWOE		1	0.5856	0.0961	37.0939	<.0001
from_US		1	1.1151	0.1797	38.5176	<.0001
money_in_title		1	2.0096	0.4630	18.8402	<.0001
mentions_salary		1	0.9984	0.1887	28.0055	<.0001
has_company_logo		1	-1.5436	0.2004	59.3067	<.0001
has_email		1	0.7796	0.3174	6.0338	0.0140

has_phone		1	0.8618	0.3686	5.4669	0.0194
has_fraud_bigram		1	1.4027	0.1531	83.9056	<.0001
has_legit_bigram		1	-0.4563	0.1444	9.9812	0.0016

Table 17: Odds ratio estimates (stepwise selection model).

Effect	Point Estimate	95% Wald Confidence Limits	
required_education Associate Degree vs. Unspecified	2.041	0.455	9.159
required_education Bachelor's Degree vs. Unspecified	1.433	0.934	2.199
required_education Certification vs. Unspecified	1.238	0.338	4.540
required_education Doctorate vs. Unspecified	<0.001	<0.001	>999.999
required_education High School or equivalent vs. Unspecified	1.304	0.857	1.984
required_education Master's Degree vs. Unspecified	5.152	2.279	11.647
required_education Professional vs. Unspecified	0.364	0.024	5.475
required_education Some college coursework vs. Unspecified	2.801	0.415	18.887
required_education Vocational vs. Unspecified	<0.001	<0.001	>999.999
company_profile_length	0.991	0.988	0.994
description_length	0.999	0.998	1.000
requirements_length	0.998	0.996	1.000
benefits_length	1.004	1.002	1.007
industry_SWOE	2.308	1.984	2.685
function_SWOE	1.796	1.488	2.168
from_US	3.050	2.145	4.337
money_in_title	7.460	3.011	18.485
mentions_salary	2.714	1.875	3.928
has_company_logo	0.214	0.144	0.316
has_email	2.181	1.171	4.062
has_phone	2.367	1.150	4.875
has_fraud_bigram	4.066	3.012	5.490
has_legit_bigram	0.634	0.477	0.841

Table 18: Model fit statistics for validation dataset (stepwise selection model).

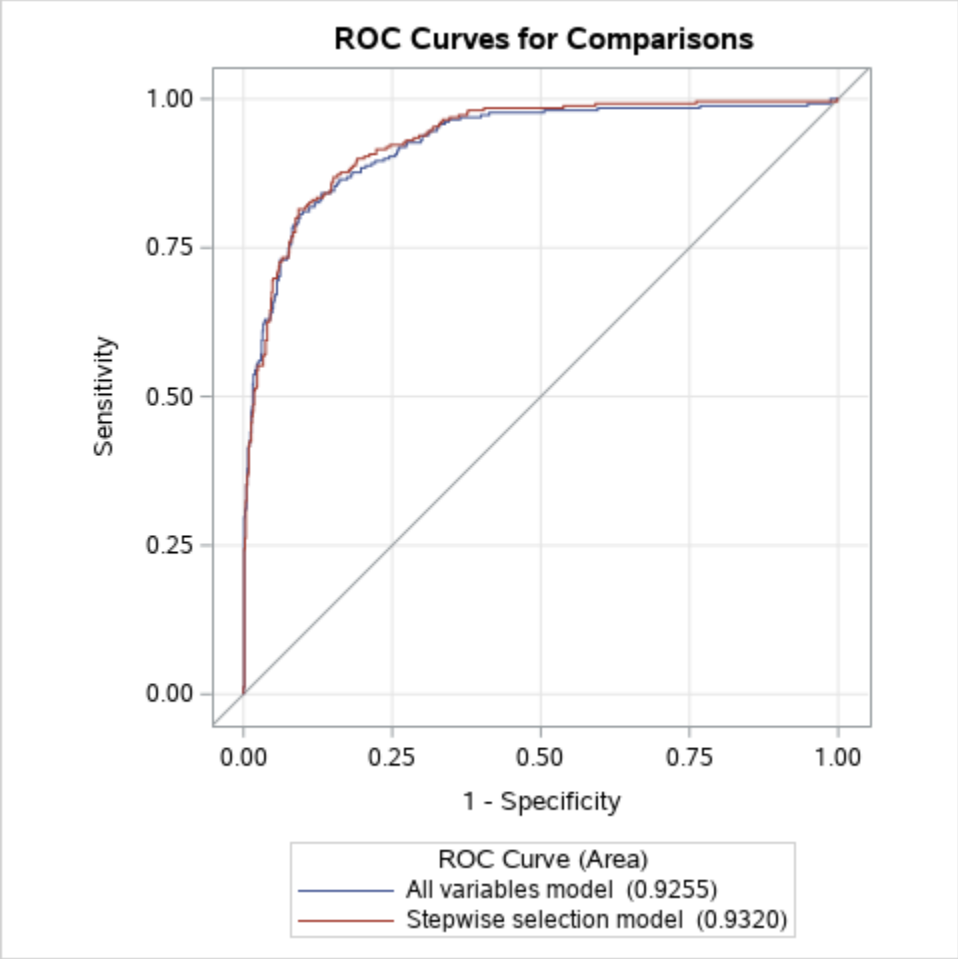
Statistic	Value
Log Likelihood	-440.6
Error Rate	0.1744
AIC	929.269
AICC	930.4536
BIC	1047.95
SC	1047.95
R-Square	0.521151
Max-Rescaled R-Square	0.655429
AUC	0.932009
Brier Score	0.12791

Comparing the Models

The last stage of the analysis was to compare the all-variables model to the stepwise selection model and pick the best model. First, looking at Tables 13 and 18, the stepwise selection model performs better than the all-variables model according to most of the model fit statistics. For example, when scoring the validation dataset, the all-variables model had an error rate of 17.53% while the stepwise selection model had an error rate of 17.44%, a small improvement. Also, the stepwise selection model has the advantage that it is more parsimonious (15 predictor variables) than the all-variables model (20 predictor variables). In general, given a group of similar models, the least complex model is preferred (Patetta, Lesson 4.1). Finally, the ROC curves of the two models were compared using the following code:

```
/* Compare ROC curves */

ods select ROCOverlay;

proc logistic data=capstone.validation;
       model fraudulent(event='1')=p_allvars p_stepwise / nofit;
       roc 'All variables model' p_allvars;
       roc 'Stepwise selection model' p_stepwise;
run;
```

Figure 23: ROC curve comparison for all-variables model and stepwise selection model.



In Figure 23, the ROC curves of the all-variables model and the stepwise selection model look very similar. However, technically speaking, the stepwise selection model does have a slightly higher AUC (0.9320) than the all-variables model (0.9255), so once again, the stepwise selection model is superior in this regard. In the end, after comparing the models with several different metrics, the stepwise selection model was chosen as the best model.

Now that a final model has been decided on, let us examine some of its features in more detail. From Table 15, the most statistically significant predictors of fraudulent status in the stepwise selection model are *company_profile_length*, *industry_SWOE*, *function_SWOE*, *from_US*, *money_in_title*, *mentions_salary*, *has_company_logo*, and *has_fraud_bigram* which

all have Wald Test p-values below 0.001. Out of the three categorical variables *employment_type, required_experience,* and *required_education* in the EMSCAD_final dataset, only *required_education* made it into the stepwise selection model. In contrast, all four of the text feature length variables *company_profile_length*, *description_length*, *requirements_length*, and *benefits_length* were found to be significant at the 5% level.

According to Table 17, the binary variables which have the highest odds ratios are *from_US*, *has_fraud_bigram*, and *money_in_title*. In particular, *from_US* has an odds ratio of 3.050 which means that the odds of a job advertisement being fraudulent are 3.050 times higher if the advertisement comes from the United States than if it comes from another country. Similarly, the odds ratio for *has_fraud_bigram* is 4.066 which means that the odds of a job advertisement being fraudulent increase by a factor of 4.066 when the advertisement contains a common fraud bigram (see pg. 25). Most impressively, the odds ratio for *money_in_title* is 7.460 which means that job advertisements which mention money in the title are 7.460 times more likely to be fraudulent than advertisements which do not. Also noteworthy is the odds ratio for *has_company_logo* which is 0.214. From this odds ratio, we can infer that the odds of a job advertisement being fraudulent decrease by 78.6% when the job advertisement displays a company logo. Likewise, the odds ratios for *company_profile_length*, *description_length*, and *requirements_length* are 0.991, 0.999, and 0.998, respectively. The fact that these odds ratios are below 1 implies that as the number of words in a job advertisement increases, the odds of the advertisement being fraudulent decrease.

CONCLUSION

Summary of Findings

In this study, the research question was, "Which features of a job advertisement can help identify whether the advertisement is fraudulent?" To answer the research question, a logistic regression model was developed using the Employment Scam Aegean Dataset, a publicly available dataset of 17,880 online job advertisements that were classified as legitimate or fraudulent by researchers at the University of the Aegean. The null hypothesis H_0 stated that there is no statistically significant association between the job advertisement features in the study and the probability of an advertisement being fraudulent while the alternative hypothesis H_a stated that there is a statistically significant association between at least one of the job advertisement features in the study and the probability of an advertisement being fraudulent. The stepwise selection model that was chosen as the best model contains 15 job advertisement features as predictors of fraudulent status which are all significant at the 5% significance level. Hence, we reject H_0 in favor of H_a. Of the 15 job advertisement features in the stepwise selection model, eight of them (*company_profile_length*, *industry_SWOE*, *function_SWOE*, *from_US*, *money_in_title*, *mentions_salary*, *has_company_logo*, and *has_fraud_bigram*) are highly significant with Wald Test p-values below 0.001. Overall, the stepwise selection model scored the validation dataset with 82.56% accuracy.

What are the main takeaways of the study? To avoid becoming the victim of a job advertisement scam, the recommended course of action is to follow the six guidelines below when researching and applying for jobs on the internet:

1. Be extremely cautious about job advertisements which mention money in the title. These advertisements were rarely encountered in the study, but when they did appear, they had

an alarmingly high fraudulent rate of 44.62% (Figure 13). In the stepwise selection model, the binary variable *money_in_title* was one of the strongest predictors of fraudulent status. According to the model, a job advertisement which mentions money in the title is 7.460 times more likely to be a scam than advertisements which do not.

2. Be wary of job advertisements which are very short and provide little information about the position. The study found that on average, fraudulent job advertisements are shorter than legitimate job advertisements when it comes to text features such as company profile, description, requirements, and benefits (Figures 8-11). In the stepwise selection model, an increase in the number of words in the advertisement decreases the odds of the advertisement being fraudulent.
3. Watch out for advertisements which contain phrases that sound too good to be true such as “No experience required!”, “Work from home!” or “Signing bonus available!” In the Text Mining section, the study found that fraudulent job advertisements frequently contain these types of phrases. In the stepwise selection model, the binary variable *has_fraud_bigram* was a highly significant predictor of fraudulent status. According to the model, if a job advertisement contains a common fraud bigram (see pg. 25 for full list), the odds of the advertisement being fraudulent increase by a factor of 4.066.
4. Look for signs that the advertisement comes from a real-life company. For example, the study found that job advertisements which have screening questions or display a company logo have lower fraudulent rates than advertisements which do not (Figures 16 & 17). In the stepwise selection model, the presence of a company logo decreases the odds of the advertisement being fraudulent by 78.6%.

5. Be cautious about advertisements which require little commitment, experience, or education. While many legitimate businesses do post advertisements for part-time or entry-level positions on the internet, the study found that these types of advertisements have higher fraudulent rates than advertisements for full-time positions requiring prior experience and college education (Figures 5-7). The categorical variable *required_education* was identified by SAS as a significant predictor of fraudulent status in the stepwise selection model.
6. Overall, be sure to exercise the same common sense when researching and applying for jobs online as with other internet activities. Do not give personal information to an online recruiter unless you are absolutely sure that they can be trusted. Fraudulent job advertisements contain email addresses and phone numbers more often than legitimate job advertisements (Figures 18 & 19). Be wary about paying a fee to submit an application—most companies do not impose them (Reinicke, 2020). Do not click on a link to an external website or download any job application software if it seems suspicious in any way.

Following these six guidelines can help the general public avoid job advertisement scams and the problems associated with them such as financial loss, identity theft, and damaged reputations.

Limitations

There were several limitations to the study which should be addressed. First, the only predictive modeling technique that was considered was logistic regression. Even though the stepwise selection model's 82.56% accuracy rate is quite good, there are many other predictive modeling techniques which could achieve better results. There might even be other logistic regression models besides the all-variables model and the stepwise selection model that were

considered which perform better. Another limitation of the study is that the job advertisements in the EMSCAD are all written in English. There is no guarantee that the results of the study will generalize to job advertisements written in other languages, especially the results of the Text Mining section. Finally, the job advertisements in the EMSCAD were released between 2012 and 2014. It is possible that fraudulent job advertisements today in the year 2021 have new characteristics which were not detected by the study.

Further Research

There are many ways in which the study could be expanded upon. First, a different predictive modelling technique could be used besides logistic regression. Past studies such as (Vidros et al., 2017) and (Kumar, 2020) have experimented with other models such as decision trees, random forests, and support vector machines with varying degrees of success. Another avenue of further research is to focus on job advertisements from one particular industry. It would be interesting to see what kinds of differences exist (if any) between fraudulent job advertisements from, say, the Information Technology sector compared to Sales & Marketing positions. Finally, as mentioned in the Limitations section, it might be beneficial to examine job advertisements from more recent years than the 2012-2014 range or job advertisements written in other languages besides English to see if the results of the study generalize to a broader set of job advertisements.

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APPENDIX

Table A: Cross tabulation of *industry* with *fraudulent*.

Frequency Percent Row % Column %	industry	fraudulent		
		0	**1**	**Total**
	Unspecified	4628 25.88 94.39 27.20	275 1.54 5.61 31.76	4903 27.42
	Information Technology and Services	1702 9.52 98.15 10.00	32 0.18 1.85 3.70	1734 9.70
	Computer Software	1371 7.67 99.64 8.06	5 0.03 0.36 0.58	1376 7.70
	Internet	1062 5.94 100.00 6.24	0 0.00 0.00 0.00	1062 5.94
	Marketing and Advertising	783 4.38 94.57 4.60	45 0.25 5.43 5.20	828 4.63
	Education Management	822 4.60 100.00 4.83	0 0.00 0.00 0.00	822 4.60
	Financial Services	744 4.16 95.51 4.37	35 0.20 4.49 4.04	779 4.36
	Hospital & Health Care	446 2.49 89.74 2.62	51 0.29 10.26 5.89	497 2.78
	Consumer Services	334 1.87 93.30 1.96	24 0.13 6.70 2.77	358 2.00

Telecommunications	316 1.77 92.40 1.86	26 0.15 7.60 3.00	342 1.91
Oil & Energy	178 1.00 62.02 1.05	109 0.61 37.98 12.59	287 1.61
Retail	218 1.22 97.76 1.28	5 0.03 2.24 0.58	223 1.25
Real Estate	151 0.84 86.29 0.89	24 0.13 13.71 2.77	175 0.98
Accounting	102 0.57 64.15 0.60	57 0.32 35.85 6.58	159 0.89
Construction	155 0.87 98.10 0.91	3 0.02 1.90 0.35	158 0.88
E-Learning	137 0.77 98.56 0.81	2 0.01 1.44 0.23	139 0.78
Management Consulting	124 0.69 95.38 0.73	6 0.03 4.62 0.69	130 0.73
Design	125 0.70 96.90 0.73	4 0.02 3.10 0.46	129 0.72
Health, Wellness and Fitness	112 0.63 88.19 0.66	15 0.08 11.81 1.73	127 0.71

Staffing and Recruiting	119 0.67 93.70 0.70	8 0.04 6.30 0.92	127 0.71
Insurance	117 0.65 95.12 0.69	6 0.03 4.88 0.69	123 0.69
Automotive	115 0.64 95.83 0.68	5 0.03 4.17 0.58	120 0.67
Logistics and Supply Chain	110 0.62 98.21 0.65	2 0.01 1.79 0.23	112 0.63
Human Resources	102 0.57 94.44 0.60	6 0.03 5.56 0.69	108 0.60
Online Media	100 0.56 99.01 0.59	1 0.01 0.99 0.12	101 0.56
Apparel & Fashion	95 0.53 97.94 0.56	2 0.01 2.06 0.23	97 0.54
Legal Services	97 0.54 100.00 0.57	0 0.00 0.00 0.00	97 0.54
Facilities Services	92 0.51 97.87 0.54	2 0.01 2.13 0.23	94 0.53
Hospitality	74 0.41 84.09 0.43	14 0.08 15.91 1.62	88 0.49

Computer Games	86 0.48 100.00 0.51	0 0.00 0.00 0.00	86 0.48
Banking	81 0.45 96.43 0.48	3 0.02 3.57 0.35	84 0.47
Building Materials	77 0.43 98.72 0.45	1 0.01 1.28 0.12	78 0.44
Leisure, Travel & Tourism	55 0.31 72.37 0.32	21 0.12 27.63 2.42	76 0.43
Nonprofit Organization Management	76 0.43 100.00 0.45	0 0.00 0.00 0.00	76 0.43
Entertainment	69 0.39 93.24 0.41	5 0.03 6.76 0.58	74 0.41
Electrical/Electronic Manufacturing	69 0.39 94.52 0.41	4 0.02 5.48 0.46	73 0.41
Food & Beverages	72 0.40 100.00 0.42	0 0.00 0.00 0.00	72 0.40
Cosmetics	64 0.36 98.46 0.38	1 0.01 1.54 0.12	65 0.36
Airlines/Aviation	62 0.35 98.41 0.36	1 0.01 1.59 0.12	63 0.35

Consumer Goods	62 0.35 98.41 0.36	1 0.01 1.59 0.12	63 0.35
Consumer Electronics	62 0.35 100.00 0.36	0 0.00 0.00 0.00	62 0.35
Medical Practice	59 0.33 98.33 0.35	1 0.01 1.67 0.12	60 0.34
Public Relations and Communications	58 0.32 100.00 0.34	0 0.00 0.00 0.00	58 0.32
Civic & Social Organization	54 0.30 98.18 0.32	1 0.01 1.82 0.12	55 0.31
Market Research	52 0.29 96.30 0.31	2 0.01 3.70 0.23	54 0.30
Transportation/Trucking/Railroad	50 0.28 94.34 0.29	3 0.02 5.66 0.35	53 0.30
Restaurants	52 0.29 100.00 0.31	0 0.00 0.00 0.00	52 0.29
Warehousing	50 0.28 98.04 0.29	1 0.01 1.96 0.12	51 0.29
Broadcast Media	49 0.27 98.00 0.29	1 0.01 2.00 0.12	50 0.28

Events Services	50 0.28 100.00 0.29	0 0.00 0.00 0.00	50 0.28
Computer & Network Security	44 0.25 89.80 0.26	5 0.03 10.20 0.58	49 0.27
Environmental Services	46 0.26 93.88 0.27	3 0.02 6.12 0.35	49 0.27
Media Production	45 0.25 93.75 0.26	3 0.02 6.25 0.35	48 0.27
Computer Networking	32 0.18 72.73 0.19	12 0.07 27.27 1.39	44 0.25
Food Production	43 0.24 97.73 0.25	1 0.01 2.27 0.12	44 0.25
Gambling & Casinos	42 0.23 100.00 0.25	0 0.00 0.00 0.00	42 0.23
Pharmaceuticals	42 0.23 100.00 0.25	0 0.00 0.00 0.00	42 0.23
Publishing	39 0.22 100.00 0.23	0 0.00 0.00 0.00	39 0.22
Biotechnology	34 0.19 89.47 0.20	4 0.02 10.53 0.46	38 0.21

Mechanical or Industrial Engineering	33 0.18 89.19 0.19	4 0.02 10.81 0.46	37 0.21
Computer Hardware	32 0.18 91.43 0.19	3 0.02 8.57 0.35	35 0.20
Utilities	32 0.18 96.97 0.19	1 0.01 3.03 0.12	33 0.18
Graphic Design	32 0.18 100.00 0.19	0 0.00 0.00 0.00	32 0.18
Printing	30 0.17 100.00 0.18	0 0.00 0.00 0.00	30 0.17
Security and Investigations	29 0.16 96.67 0.17	1 0.01 3.33 0.12	30 0.17
Research	29 0.16 100.00 0.17	0 0.00 0.00 0.00	29 0.16
Venture Capital & Private Equity	29 0.16 100.00 0.17	0 0.00 0.00 0.00	29 0.16
Information Services	26 0.15 92.86 0.15	2 0.01 7.14 0.23	28 0.16
Aviation & Aerospace	24 0.13 100.00 0.14	0 0.00 0.00 0.00	24 0.13

Farming	24 0.13 100.00 0.14	0 0.00 0.00 0.00	24 0.13
Mental Health Care	23 0.13 100.00 0.14	0 0.00 0.00 0.00	23 0.13
Sports	23 0.13 100.00 0.14	0 0.00 0.00 0.00	23 0.13
Chemicals	22 0.12 100.00 0.13	0 0.00 0.00 0.00	22 0.12
Government Administration	22 0.12 100.00 0.13	0 0.00 0.00 0.00	22 0.12
Law Practice	19 0.11 100.00 0.11	0 0.00 0.00 0.00	19 0.11
Medical Devices	18 0.10 94.74 0.11	1 0.01 5.26 0.12	19 0.11
Outsourcing/Offshoring	18 0.10 94.74 0.11	1 0.01 5.26 0.12	19 0.11
Writing and Editing	19 0.11 100.00 0.11	0 0.00 0.00 0.00	19 0.11
Business Supplies and Equipment	15 0.08 83.33 0.09	3 0.02 16.67 0.35	18 0.10

Fund-Raising	16 0.09 100.00 0.09	0 0.00 0.00 0.00	16 0.09
Professional Training & Coaching	14 0.08 100.00 0.08	0 0.00 0.00 0.00	14 0.08
Government Relations	11 0.06 100.00 0.06	0 0.00 0.00 0.00	11 0.06
Higher Education	11 0.06 100.00 0.06	0 0.00 0.00 0.00	11 0.06
Machinery	11 0.06 100.00 0.06	0 0.00 0.00 0.00	11 0.06
Semiconductors	11 0.06 100.00 0.06	0 0.00 0.00 0.00	11 0.06
Wholesale	10 0.06 90.91 0.06	1 0.01 9.09 0.12	11 0.06
Architecture & Planning	10 0.06 100.00 0.06	0 0.00 0.00 0.00	10 0.06
Law Enforcement	10 0.06 100.00 0.06	0 0.00 0.00 0.00	10 0.06
Music	10 0.06 100.00 0.06	0 0.00 0.00 0.00	10 0.06

Translation and Localization	10 0.06 100.00 0.06	0 0.00 0.00 0.00	10 0.06
Civil Engineering	8 0.04 88.89 0.05	1 0.01 11.11 0.12	9 0.05
Defense & Space	7 0.04 77.78 0.04	2 0.01 22.22 0.23	9 0.05
Individual & Family Services	9 0.05 100.00 0.05	0 0.00 0.00 0.00	9 0.05
Program Development	9 0.05 100.00 0.05	0 0.00 0.00 0.00	9 0.05
Renewables & Environment	9 0.05 100.00 0.05	0 0.00 0.00 0.00	9 0.05
Executive Office	6 0.03 75.00 0.04	2 0.01 25.00 0.23	8 0.04
International Trade and Development	8 0.04 100.00 0.05	0 0.00 0.00 0.00	8 0.04
Veterinary	8 0.04 100.00 0.05	0 0.00 0.00 0.00	8 0.04
Industrial Automation	7 0.04 100.00 0.04	0 0.00 0.00 0.00	7 0.04

Photography	7 0.04 100.00 0.04	0 0.00 0.00 0.00	7 0.04
Public Safety	6 0.03 85.71 0.04	1 0.01 14.29 0.12	7 0.04
Investment Management	5 0.03 83.33 0.03	1 0.01 16.67 0.12	6 0.03
Motion Pictures and Film	6 0.03 100.00 0.04	0 0.00 0.00 0.00	6 0.03
Primary/Secondary Education	6 0.03 100.00 0.04	0 0.00 0.00 0.00	6 0.03
Religious Institutions	6 0.03 100.00 0.04	0 0.00 0.00 0.00	6 0.03
Animation	3 0.02 60.00 0.02	2 0.01 40.00 0.23	5 0.03
Capital Markets	5 0.03 100.00 0.03	0 0.00 0.00 0.00	5 0.03
Import and Export	5 0.03 100.00 0.03	0 0.00 0.00 0.00	5 0.03
Package/Freight Delivery	5 0.03 100.00 0.03	0 0.00 0.00 0.00	5 0.03

Packaging and Containers	5 0.03 100.00 0.03	0 0.00 0.00 0.00	5 0.03
Commercial Real Estate	4 0.02 100.00 0.02	0 0.00 0.00 0.00	4 0.02
Fishery	4 0.02 100.00 0.02	0 0.00 0.00 0.00	4 0.02
Investment Banking	4 0.02 100.00 0.02	0 0.00 0.00 0.00	4 0.02
Luxury Goods & Jewelry	4 0.02 100.00 0.02	0 0.00 0.00 0.00	4 0.02
Philanthropy	4 0.02 100.00 0.02	0 0.00 0.00 0.00	4 0.02
Wireless	4 0.02 100.00 0.02	0 0.00 0.00 0.00	4 0.02
Furniture	3 0.02 100.00 0.02	0 0.00 0.00 0.00	3 0.02
Maritime	3 0.02 100.00 0.02	0 0.00 0.00 0.00	3 0.02
Mining & Metals	3 0.02 100.00 0.02	0 0.00 0.00 0.00	3 0.02

Performing Arts	3 0.02 100.00 0.02	0 0.00 0.00 0.00	3 0.02
Plastics	3 0.02 100.00 0.02	0 0.00 0.00 0.00	3 0.02
Public Policy	3 0.02 100.00 0.02	0 0.00 0.00 0.00	3 0.02
Libraries	2 0.01 100.00 0.01	0 0.00 0.00 0.00	2 0.01
Military	1 0.01 50.00 0.01	1 0.01 50.00 0.12	2 0.01
Nanotechnology	2 0.01 100.00 0.01	0 0.00 0.00 0.00	2 0.01
Textiles	2 0.01 100.00 0.01	0 0.00 0.00 0.00	2 0.01
Alternative Dispute Resolution	1 0.01 100.00 0.01	0 0.00 0.00 0.00	1 0.01
Museums and Institutions	1 0.01 100.00 0.01	0 0.00 0.00 0.00	1 0.01
Ranching	0 0.00 0.00 0.00	1 0.01 100.00 0.12	1 0.01

Shipbuilding	1 0.01 100.00 0.01	0 0.00 0.00 0.00	1 0.01
Sporting Goods	1 0.01 100.00 0.01	0 0.00 0.00 0.00	1 0.01
Wine and Spirits	1 0.01 100.00 0.01	0 0.00 0.00 0.00	1 0.01
Total	17014 95.16	866 4.84	17880 100.00

Table B: Cross tabulation of *function* with *fraudulent*.

Frequency Percent Row % Column %	**function**	**fraudulent**		
		0	**1**	**Total**
	Unspecified	6118 34.22 94.78 35.96	337 1.88 5.22 38.91	6455 36.10
	Information Technology	1717 9.60 98.17 10.09	32 0.18 1.83 3.70	1749 9.78
	Sales	1427 7.98 97.21 8.39	41 0.23 2.79 4.73	1468 8.21
	Engineering	1235 6.91 91.62 7.26	113 0.63 8.38 13.05	1348 7.54
	Customer Service	1162 6.50 94.55 6.83	67 0.37 5.45 7.74	1229 6.87
	Marketing	820 4.59 98.80 4.82	10 0.06 1.20 1.15	830 4.64
	Administrative	511 2.86 81.11 3.00	119 0.67 18.89 13.74	630 3.52
	Design	337 1.88 99.12 1.98	3 0.02 0.88 0.35	340 1.90
	Health Care Provider	337 1.88 99.70 1.98	1 0.01 0.30 0.12	338 1.89

Education	324 1.81 99.69 1.90	1 0.01 0.31 0.12	325 1.82
Other	293 1.64 90.15 1.72	32 0.18 9.85 3.70	325 1.82
Management	311 1.74 98.11 1.83	6 0.03 1.89 0.69	317 1.77
Business Development	215 1.20 94.30 1.26	13 0.07 5.70 1.50	228 1.28
Accounting/Auditing	183 1.02 86.32 1.08	29 0.16 13.68 3.35	212 1.19
Human Resources	196 1.10 95.61 1.15	9 0.05 4.39 1.04	205 1.15
Project Management	173 0.97 94.54 1.02	10 0.06 5.46 1.15	183 1.02
Finance	157 0.88 91.28 0.92	15 0.08 8.72 1.73	172 0.96
Consulting	140 0.78 97.22 0.82	4 0.02 2.78 0.46	144 0.81
Art/Creative	131 0.73 99.24 0.77	1 0.01 0.76 0.12	132 0.74

Writing/Editing	132 0.74 100.00 0.78	0 0.00 0.00 0.00	132 0.74
Production	116 0.65 100.00 0.68	0 0.00 0.00 0.00	116 0.65
Product Management	114 0.64 100.00 0.67	0 0.00 0.00 0.00	114 0.64
Quality Assurance	111 0.62 100.00 0.65	0 0.00 0.00 0.00	111 0.62
Advertising	85 0.48 94.44 0.50	5 0.03 5.56 0.58	90 0.50
Business Analyst	83 0.46 98.81 0.49	1 0.01 1.19 0.12	84 0.47
Data Analyst	78 0.44 95.12 0.46	4 0.02 4.88 0.46	82 0.46
Public Relations	75 0.42 98.68 0.44	1 0.01 1.32 0.12	76 0.43
Manufacturing	72 0.40 97.30 0.42	2 0.01 2.70 0.23	74 0.41
General Business	67 0.37 98.53 0.39	1 0.01 1.47 0.12	68 0.38

Research	50 0.28 100.00 0.29	0 0.00 0.00 0.00	50 0.28
Legal	47 0.26 100.00 0.28	0 0.00 0.00 0.00	47 0.26
Strategy/Planning	45 0.25 97.83 0.26	1 0.01 2.17 0.12	46 0.26
Training	38 0.21 100.00 0.22	0 0.00 0.00 0.00	38 0.21
Supply Chain	36 0.20 100.00 0.21	0 0.00 0.00 0.00	36 0.20
Financial Analyst	28 0.16 84.85 0.16	5 0.03 15.15 0.58	33 0.18
Distribution	21 0.12 87.50 0.12	3 0.02 12.50 0.35	24 0.13
Purchasing	15 0.08 100.00 0.09	0 0.00 0.00 0.00	15 0.08
Science	14 0.08 100.00 0.08	0 0.00 0.00 0.00	14 0.08
Total	17014 95.16	866 4.84	17880 100.00

Table C: Cross tabulation of *country* with *fraudulent*.

Frequency Percent Row % Column %	fraudulent		
country	**0**	**1**	**Total**
US	9926 55.51 93.15 58.34	730 4.08 6.85 84.30	10656 59.60
GB	2361 13.20 99.04 13.88	23 0.13 0.96 2.66	2384 13.33
GR	940 5.26 100.00 5.52	0 0.00 0.00 0.00	940 5.26
CA	445 2.49 97.37 2.62	12 0.07 2.63 1.39	457 2.56
DE	383 2.14 100.00 2.25	0 0.00 0.00 0.00	383 2.14
Unspecified	327 1.83 94.51 1.92	19 0.11 5.49 2.19	346 1.94
NZ	333 1.86 100.00 1.96	0 0.00 0.00 0.00	333 1.86
IN	272 1.52 98.55 1.60	4 0.02 1.45 0.46	276 1.54
AU	174 0.97 81.31 1.02	40 0.22 18.69 4.62	214 1.20

PH	131 0.73 99.24 0.77	1 0.01 0.76 0.12	132 0.74
NL	127 0.71 100.00 0.75	0 0.00 0.00 0.00	127 0.71
BE	117 0.65 100.00 0.69	0 0.00 0.00 0.00	117 0.65
IE	114 0.64 100.00 0.67	0 0.00 0.00 0.00	114 0.64
SG	80 0.45 100.00 0.47	0 0.00 0.00 0.00	80 0.45
HK	77 0.43 100.00 0.45	0 0.00 0.00 0.00	77 0.43
PL	73 0.41 96.05 0.43	3 0.02 3.95 0.35	76 0.43
EE	71 0.40 98.61 0.42	1 0.01 1.39 0.12	72 0.40
IL	72 0.40 100.00 0.42	0 0.00 0.00 0.00	72 0.40
FR	70 0.39 100.00 0.41	0 0.00 0.00 0.00	70 0.39

ES	65 0.36 98.48 0.38	1 0.01 1.52 0.12	66 0.37
AE	53 0.30 98.15 0.31	1 0.01 1.85 0.12	54 0.30
EG	51 0.29 98.08 0.30	1 0.01 1.92 0.12	52 0.29
SE	49 0.27 100.00 0.29	0 0.00 0.00 0.00	49 0.27
RO	46 0.26 100.00 0.27	0 0.00 0.00 0.00	46 0.26
DK	42 0.23 100.00 0.25	0 0.00 0.00 0.00	42 0.23
ZA	39 0.22 97.50 0.23	1 0.01 2.50 0.12	40 0.22
BR	35 0.20 97.22 0.21	1 0.01 2.78 0.12	36 0.20
IT	31 0.17 100.00 0.18	0 0.00 0.00 0.00	31 0.17
FI	29 0.16 100.00 0.17	0 0.00 0.00 0.00	29 0.16

PK	26 0.15 96.30 0.15	1 0.01 3.70 0.12	27 0.15
LT	23 0.13 100.00 0.14	0 0.00 0.00 0.00	23 0.13
MY	9 0.05 42.86 0.05	12 0.07 57.14 1.39	21 0.12
QA	15 0.08 71.43 0.09	6 0.03 28.57 0.69	21 0.12
JP	20 0.11 100.00 0.12	0 0.00 0.00 0.00	20 0.11
RU	20 0.11 100.00 0.12	0 0.00 0.00 0.00	20 0.11
MX	18 0.10 100.00 0.11	0 0.00 0.00 0.00	18 0.10
PT	18 0.10 100.00 0.11	0 0.00 0.00 0.00	18 0.10
BG	17 0.10 100.00 0.10	0 0.00 0.00 0.00	17 0.10
TR	17 0.10 100.00 0.10	0 0.00 0.00 0.00	17 0.10

CH	15 0.08 100.00 0.09	0 0.00 0.00 0.00	15 0.08
CN	15 0.08 100.00 0.09	0 0.00 0.00 0.00	15 0.08
SA	14 0.08 93.33 0.08	1 0.01 6.67 0.12	15 0.08
AT	14 0.08 100.00 0.08	0 0.00 0.00 0.00	14 0.08
HU	14 0.08 100.00 0.08	0 0.00 0.00 0.00	14 0.08
MU	14 0.08 100.00 0.08	0 0.00 0.00 0.00	14 0.08
ID	12 0.07 92.31 0.07	1 0.01 7.69 0.12	13 0.07
MT	13 0.07 100.00 0.08	0 0.00 0.00 0.00	13 0.07
UA	13 0.07 100.00 0.08	0 0.00 0.00 0.00	13 0.07
CY	11 0.06 100.00 0.06	0 0.00 0.00 0.00	11 0.06

IQ	10 0.06 100.00 0.06	0 0.00 0.00 0.00	10 0.06
KR	10 0.06 100.00 0.06	0 0.00 0.00 0.00	10 0.06
NG	10 0.06 100.00 0.06	0 0.00 0.00 0.00	10 0.06
TH	10 0.06 100.00 0.06	0 0.00 0.00 0.00	10 0.06
AR	9 0.05 100.00 0.05	0 0.00 0.00 0.00	9 0.05
BH	4 0.02 44.44 0.02	5 0.03 55.56 0.58	9 0.05
BY	9 0.05 100.00 0.05	0 0.00 0.00 0.00	9 0.05
LU	9 0.05 100.00 0.05	0 0.00 0.00 0.00	9 0.05
PA	9 0.05 100.00 0.05	0 0.00 0.00 0.00	9 0.05
NO	8 0.04 100.00 0.05	0 0.00 0.00 0.00	8 0.04

KE	7 0.04 100.00 0.04	0 0.00 0.00 0.00	7 0.04
RS	7 0.04 100.00 0.04	0 0.00 0.00 0.00	7 0.04
CZ	6 0.03 100.00 0.04	0 0.00 0.00 0.00	6 0.03
LV	6 0.03 100.00 0.04	0 0.00 0.00 0.00	6 0.03
NI	4 0.02 100.00 0.02	0 0.00 0.00 0.00	4 0.02
TT	4 0.02 100.00 0.02	0 0.00 0.00 0.00	4 0.02
TW	2 0.01 50.00 0.01	2 0.01 50.00 0.23	4 0.02
VN	4 0.02 100.00 0.02	0 0.00 0.00 0.00	4 0.02
VI	3 0.02 100.00 0.02	0 0.00 0.00 0.00	3 0.02
AM	2 0.01 100.00 0.01	0 0.00 0.00 0.00	2 0.01

BD	2 0.01 100.00 0.01	0 0.00 0.00 0.00	2 0.01
CL	2 0.01 100.00 0.01	0 0.00 0.00 0.00	2 0.01
IS	2 0.01 100.00 0.01	0 0.00 0.00 0.00	2 0.01
KW	2 0.01 100.00 0.01	0 0.00 0.00 0.00	2 0.01
LK	2 0.01 100.00 0.01	0 0.00 0.00 0.00	2 0.01
SK	2 0.01 100.00 0.01	0 0.00 0.00 0.00	2 0.01
TN	2 0.01 100.00 0.01	0 0.00 0.00 0.00	2 0.01
ZM	2 0.01 100.00 0.01	0 0.00 0.00 0.00	2 0.01
AL	1 0.01 100.00 0.01	0 0.00 0.00 0.00	1 0.01
CM	1 0.01 100.00 0.01	0 0.00 0.00 0.00	1 0.01

CO	1 0.01 100.00 0.01	0 0.00 0.00 0.00	1 0.01
GH	1 0.01 100.00 0.01	0 0.00 0.00 0.00	1 0.01
HR	1 0.01 100.00 0.01	0 0.00 0.00 0.00	1 0.01
JM	1 0.01 100.00 0.01	0 0.00 0.00 0.00	1 0.01
KH	1 0.01 100.00 0.01	0 0.00 0.00 0.00	1 0.01
KZ	1 0.01 100.00 0.01	0 0.00 0.00 0.00	1 0.01
MA	1 0.01 100.00 0.01	0 0.00 0.00 0.00	1 0.01
PE	1 0.01 100.00 0.01	0 0.00 0.00 0.00	1 0.01
SD	1 0.01 100.00 0.01	0 0.00 0.00 0.00	1 0.01
SI	1 0.01 100.00 0.01	0 0.00 0.00 0.00	1 0.01
SV	1	0	1

	0.01 100.00 0.01	0.00 0.00 0.00	0.01
UG	1 0.01 100.00 0.01	0 0.00 0.00 0.00	1 0.01
Total	17014 95.16	866 4.84	17880 100.00