Predicting Salaries From Job Descriptions

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December 2, 2014

1 Introduction

Under the context of natural language processing, this lab explores the relation between job descriptions and salaries. This topic was the focus of a Kaggle competition whose sponsor, Adzuna, had a database of job listings of which only half provided salary information (the winner received $3000). As applicants will more likely apply to descriptions that give a salary, Adzuna's placement rate (and hence revenue) is improved if they can provide an estimated salary for those descriptions that did not originally include one. The employee recruiting business is structured so that Adzuna generally can't directly ask the companies to provide salary estimates. This is challenging from the legal standpoint, as grossly incorrect salaries may expose Adzuna to claims from applicants and companies, and applicant experience, since Adzuna's estimates must seem plausible to applicants before they will be willing to spend the time applying.

While Adzuna could manually estimate these salaries, scalability encourages throwing computers at the problem. In this lab we will be using Adzuna's job description and salary datasets, divided into training and test sets. These descriptions vary in word count, industry, employment level, and company location, while the salaries are the mean of the provided salary range. The variability in description content leads to notoriously sparse matrices, so we will be interested in the tradeoffs of various feature descriptors. The naive approach to this problem is to count the occurrences of individual words and associate them to salaries; here each word is a feature and as there are many descriptive words the resulting matrices will be sparse. Other feature choices may be individual word length, occurrences of word pairs or triplets (i.e. "technical communication"), n-grams (sequences of n characters), and many others. It is common to ignore stop words like "the","a","it","you","we", etc. because they add little information.

2 Warm-Up

Our goal in the warm-up is to use two job descriptions with known salaries to predict the salary of another job given the description. Here are two examples from the dataset:

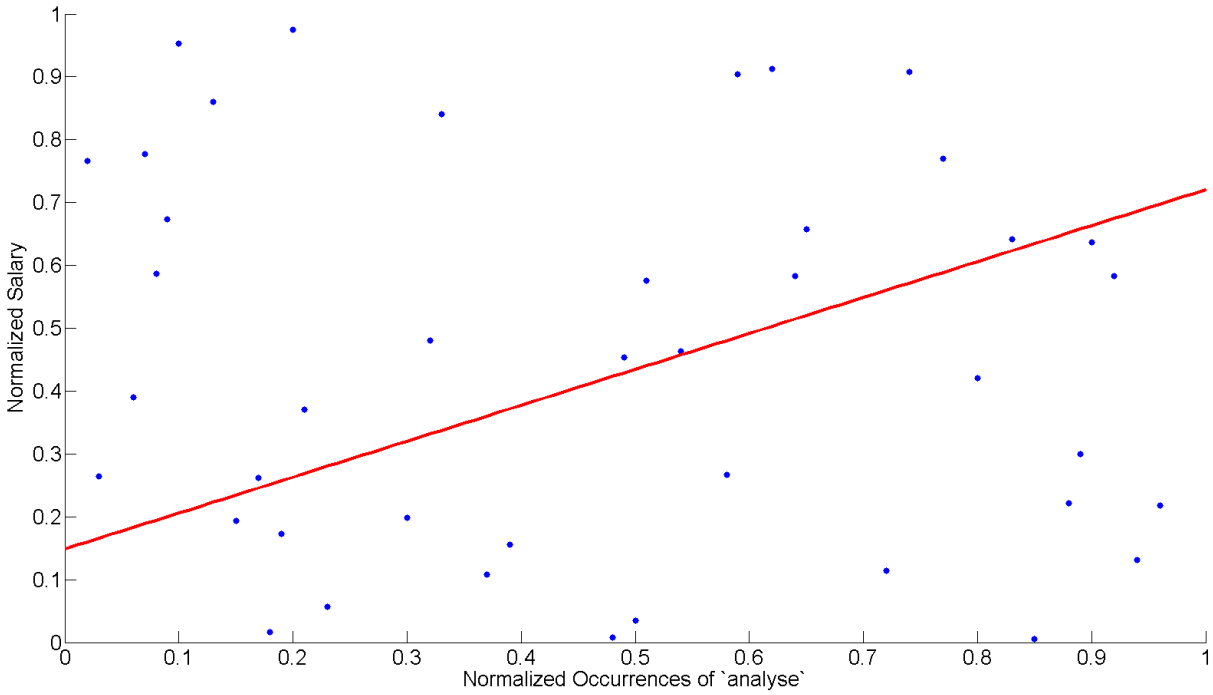
> `Engineering Systems Analyst Dorking Surrey Salary ****K Our client is located in Dorking, Surrey and are looking for Engineering Systems Analyst our client provides specialist software development Keywords Mathematical Modelling, Risk Analysis, System Modelling, Optimisation, MISER, PIONEEER Engineering Systems Analyst Dorking Surrey Salary ****K`

with a salary of $25,000 and

> `A subsea engineering company is looking for an experienced Subsea Cable Engineer who will be responsible for providing all issues related to cables. They will need someone who has at least 1015 years of subsea cable engineering experience with significant experience within offshore oil and gas industries. The qualified candidate will be responsible for developing new modelling methods for FEA and CFD. You will also be providing technical leadership to all staff therefore you must be an expert in problem solving and risk assessments. You must also be proactive and must have strong interpersonal skills. You must be a Chartered Engineer or working towards it the qualification. The company offers an extremely competitive salary, health care plan, training, professional membership sponsorship, and relocation package`

having a salary of $85,000.

One method to predict the salary from another description is least squares estimation. Least squares estimation can be thought of as an optimization problem which aims to minimize the error estimated and measured data. In our case, we want to predict salaries from the words contained in the job descriptions. For now, let's consider only occurrences of "analyse" in the description. If you plot the number of occurrences against the job salary, you might produce something like



In solving the least squared problem, we're looking for the line which passes nearest to all of the points, as measured by the Euclidean distance, or

$$error = \sqrt{(x_i - x_L)^2 + (y_i - y_L)^2} \tag{1}$$

If we considered two words, say "analyse" and "qualified", we would now have a 3D space to find our least squared solution with one axis being occurrences of "analyse," another "qualified," and the third the salary. Here, our solution will be a plane that slices the 3D space; adding more words - or features as they're more generally described - increases the dimensionality of this space, and our solution becomes a hyperplane. In all cases, we want to minimize the distance from all of the data points to the lower-dimensional estimate.

We would like to determine the words that best predict salary, or even better the frequency of the words which best predict salary. Here we show the 11 most common words for each description:

Description 1		Description 2	
****k	2	1015	1
analysis	1	a	2
analyst	3	all	2
and	1	also	2
are	1	an	3
client	2	and	5
development	1	assessments	1
dorking	3	at	1
engineering	3	be	6
for	1	cable	2
in	1	cables	1

We can collect these word counts into the matrix $\boldsymbol{A}$, and the salaries into the vector $\boldsymbol{b}$. $\boldsymbol{A}$ will have 2 rows, one for each description and as many columns as there are unique words between the two descriptions. $\boldsymbol{b}$ will have 2 rows, one salary for each description, and one column. $\boldsymbol{A}$ and $\boldsymbol{b}$ will look like the following

$$\boldsymbol{A} = \begin{bmatrix} 2 & 0 & 0 & 0 & 0 & 0 & 1 & 3 & 1 & 1 \cdots \\ 0 & 1 & 2 & 2 & 2 & 3 & 0 & 0 & 5 & 0 \cdots \end{bmatrix}$$

$$\boldsymbol{b} = \begin{bmatrix} 25000 \\ 85000 \end{bmatrix}$$

with the first 2 corresponding to the two occurrences of '****k' in the first descripton and the later 1, 5 column to occurrences of 'and' in both descriptions.

We can then set up our problem as

$$\boldsymbol{b} = \boldsymbol{A}\boldsymbol{x} \tag{2}$$

where $\boldsymbol{x}$ contains the weights (importance) of each word in predicting the salary of the job. We can find a solution for $\boldsymbol{x}$, $\hat{\boldsymbol{x}}$, by minimizing the residual errors between $\boldsymbol{b}$ and $\boldsymbol{A}\boldsymbol{x}$. This is the same as minimizing the sum of squared residuals,

$$\|\boldsymbol{b} - \boldsymbol{A}\boldsymbol{x}\|_2^2 \tag{3}$$

This optimization has a well-known solution for $\hat{\boldsymbol{x}}$

$$\hat{\boldsymbol{x}} = (\boldsymbol{A}^T\boldsymbol{A})^{-1}\boldsymbol{A}^T\boldsymbol{b} \tag{4}$$

when $\boldsymbol{A}$ is positive semidefinite and invertible.

In cases when $\boldsymbol{A}$ is not positive semidefinite, as in the $\boldsymbol{A}$ derived from the word counts above, we can use the right psuedo-inverse of $\boldsymbol{A}$. In Matlab this is

$$\hat{\boldsymbol{x}} = \texttt{pinv}(\boldsymbol{A}) * \boldsymbol{b} \tag{5}$$

The least squares solution to this problem is

$$\hat{\boldsymbol{x}} = \begin{bmatrix} 1819.6517 \\ 1730.9558 \\ 1427.6805 \\ 1250.2887 \\ 1213.1011 \\ 1213.1011 \\ 1213.1011 \\ 909.8258 \\ 909.8258 \\ 909.8258 \\ 732.4341 \\ \vdots \end{bmatrix} \begin{array}{l} \text{“}be\text{” from } [0, 6] \\ \text{“}and\text{” from } [1, 5] \\ \text{“}for\text{” from } [1, 4] \\ \text{“}engineering\text{” from } [3, 2] \\ \text{“}must\text{” from } [0, 4] \\ \text{“}will\text{” from } [0, 4] \\ \text{“}you\text{” from } [0, 4] \\ \text{“}an\text{” from } [0, 3] \\ \text{“}subsea\text{” from } [0, 3] \\ \text{“}the\text{” from } [0, 3] \\ \text{“}modelling\text{” from } [2, 1] \\ \vdots \end{array}$$

The bracketed numbers give the number of occurrences of that word in each of the descriptions; with only two samples it should not be surprising that the most heavily-weighted words are unique to each description. But notice how some words are identically-weighted and that from these 11 ‘most important’ words, none of them are highly descriptive.

Activity 1

Construct the above $\boldsymbol{A}$ and $\boldsymbol{b}$ matrices using the 1st and 2nd descriptions in the warm-up data, warmup_train.mat. $\boldsymbol{A}$ should be a $2\times m$ matrix where m is the number of unique words between the two descriptions. $\boldsymbol{b}$ should be a 2×1 matrix. Can you reproduce the above solution for $\hat{\boldsymbol{x}}$? Report on the uniqueness of the solution for $\hat{\boldsymbol{x}}$ in this problem. Support your conclusion.

The following commands may be helpful:

```
word = strrep('word','charactersToReplace','replaceThemWith')
parts = strsplit('sentence')
lowercase = lower('UpperCase')
uwords = unique(wordArray)
sortedArray = sort(unsortedArray)
```

Next we wish to predict the salary of another description using our $\hat{\boldsymbol{x}}$.

> Our client is part of an international hotel chain that require an experienced Cluster Revenue Manager to be based in Hertfordshire. The Cluster Revenue Manager will drive and influence revenue for three to four hotels. As Cluster Revenue Manager you will maximise revenue, market share and profits for multiple hotels through the strategic coordination of revenue management processes and procedures. The Cluster Revenue Manager will drive the continued development and growth of customer service standards, revenue and profits from multiple hotels and to deliver the companys mission relating to profit, people, customer and quality. You will currently be a Cluster Revenue Manager or a Regional/ Area Revenue Manager looking after a minimum of two propertys or a Revenue Manager in a large unit managing both rooms and conference space. This job was originally posted as www.caterer.com/JobSeeking/ClusterRevenueManager_job****

having a salary of $45,000.

Activity 2

Use your solution for $\hat{\boldsymbol{x}}$ in Activity 1 to estimate the salary of the third description in the warm-up test data, warmup_test.mat. Since $\hat{\boldsymbol{x}}$ is a weighting of words from the first two descriptions, ignore any words that are unique to the third description.

We now construct the matrix $\boldsymbol{A}$ for this description. This matrix will only contain frequencies of words that were present in the previous two descriptions, so many words in this new description will be left out. We can then use our weights for best predicting words, $\hat{\boldsymbol{x}}$ to estimate the salary of the job for this new description, now contained in the matrix $\boldsymbol{b}$. Our estimated salary will be stored in $\hat{\boldsymbol{b}}$, which we estimate from Equation 2.

The estimated salary is \$3,032.80. About \$41,967 different from the true salary associated with the job. Would Adzuna likely use this technique of linear least squares? Consider how populated our $\boldsymbol{A}$ matrix is for the third description. Is the matrix well-populated or sparsely-populated? Based on your intuition, are all of the words in $\hat{\boldsymbol{x}}$ likely to be good predictors of salary? How might paring down the keywords in our data matrix benefit us? In the following sections we will introduce ways to include many more descriptions in our analysis, and derive more accurate predictors of a salary based on the description.

3 Feature Descriptors / Regularized LS - Elijah

About a page... Have them solve a 10 description problem w/ and w/o regularization?

4 The Lasso Method - Ahmed

Describe Lasso briefly, that it's a regularized method which 'works better' for this sparse problem.. Solve same 10 problem with Lasso Provide A, A inv, and xhat for a larger problem?

5 Using the Results...Ben

We've seen that accurate salary prediction is a function of the algorithm and the size of the training set, and while there are many additional improvements, let's conclude by exploring some results of this analysis.

Recall that the basic form of the least squares problem is $\boldsymbol{b} = \boldsymbol{A}\boldsymbol{x}$. We formed $\boldsymbol{A}$ by counting the number of occurrences of each word in the job description and placed the corresponding salaries in $\boldsymbol{b}$. $\boldsymbol{A}$ can be viewed as a mapping from word-weight space (home of $\boldsymbol{x}$) to salary space, with the reverse mapping coming from $\boldsymbol{A}$'s inverse. $\boldsymbol{x}$ was then the weight or descriptiveness of each word - how useful its number of occurrences were in predicting the correct salary.

$\boldsymbol{A}$ is a linear operator, so if a particular applicant wants to make \$50,000, we can determine which words they should look for when reading descriptions by computing $\boldsymbol{sum}(\texttt{pinv}(\boldsymbol{A})\mathbf{50000, 2})$. If the applicant includes these descriptive words in their objective statement or elsewhere in their resume, it is reasonable to expect that their application will be successful (though this is a different - if similar - problem). We can also use the $\boldsymbol{A}$ and $\boldsymbol{x}$ computed from the training data to analyze a resume and suggest what salary their resume implicitly seeks.

clustering graph...

6 Conclusion