University Brands Experiment

Samir Datta, Nishanth Nair, Kim Vignola, Kathleen Wang
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Abstract

In this study we explored how University brand may impact initial contacts on LinkedIn, focusing on higher cost ("brand") versus lower cost ("non-brand") public Universities. To explore this question, we applied to nearly 150 jobs on LinkedIn with two different resumes (one "strong" and one "weak"). The strong resume was defined as having leadership qualities whereas the "weak" resume was a decidedly more casual, lacking leadership credentials. We could not reject the null hypothesis that all schools have the same opportunity of being contacted by potential employers. Our 2x2 experimental design, however, did allow us to glean that lower-cost (and lower-ranked) schools may be buoyed by a strong leadership resume. While the reverse also seems to be true -- higher cost schools perform better with a "weaker" resume -- it is unclear whether this is due to a truly "weak" resume or another omitted variable. It is a promising indicator that employers are open to students from lower cost (and lower ranked) schools, especially when these students make a strong case for themselves.

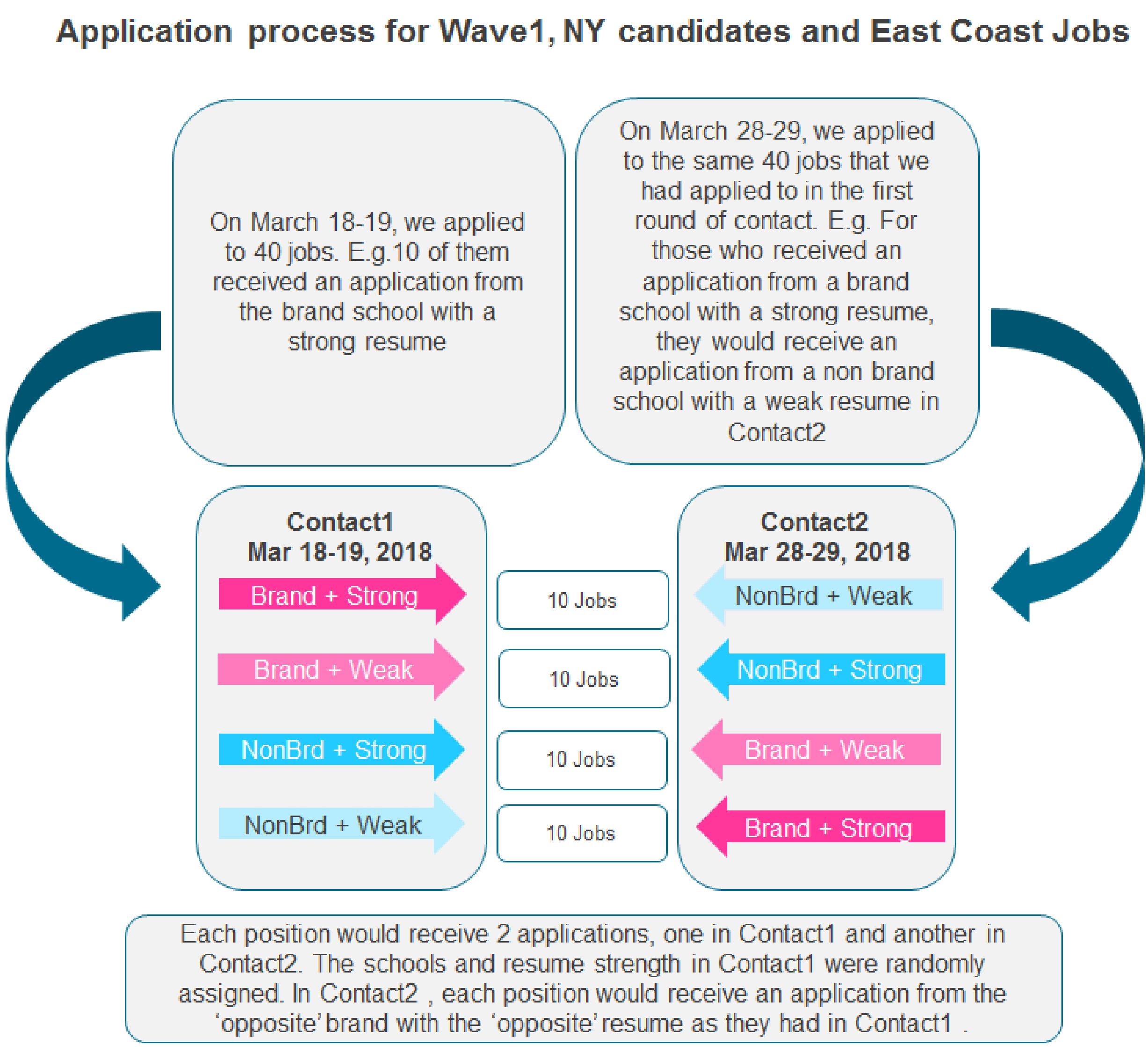
Introduction

As the costs of attending college soar, more and more attention is being paid to the cost/benefit tradeoff of attending different schools. While most prospective students evaluate school rankings and expected starting salaries, recruitment strength has yet to be quantified. Specifically, social media sites such as LinkedIn have become primary avenues of recruitment, but we don't know how one school fares better than another in that arena. While we might expect that top tier schools such as Stanford, Harvard and MIT will quickly open doors in all areas of recruitment, the difference between schools with less firepower is unclear. In California, the UCs (Universities of California) are generally more prestigious than the Cal State Universities, but costs are also higher. For example, UCLA is ranked higher than CSU Long Beach on US News World Report's rankings of engineering schools" (18 vs. 137), but it also costs more than twice the tuition to attend ($13.2K vs. $6.5K annually). The primary question we set out to answer was: *Does attending a higher cost public University result in more initial opportunity on recruitment sites such as LinkedIn?*

Experimental Design

The following sections capture the complex experimental design for this project. We first defined our outcome as the difference between call back rates based on school brand and resume strength. Then we selected four colleges, two on the East Coast and two on the West Coast. We selected these two areas for their abundant job opportunities. We then created four candidates, one from each college. The team went to great length to make sure the virtual candidates appear as real as possible. Then we created weak and strong resumes for each candidate. The strong resumes were identical except for candidate names, with the same leadership, internship and career experiences; the weak resumes have less leadership experience and less prestige career achievement.

With the basic setup in place, the next phase for the team was to find job positions, randomize and apply to each job. We approached this in two phases, leaving some time between phases for new job postings to open up. In total, we identified 150 jobs for both coasts combined. Our NY candidates only applied to the 70 East Coast jobs whereas our LA candidates only applied to the 80 West Coast jobs. The diagram below illustrates the application process for phase 1 NY applications only. The same process was followed for the West Coast and for both Coasts in phase 2.



For each phase, we further split the application process into two rounds of contacts. As illustrated in the above diagram, Contact2 happened a few days after Contact1. This is designed to reduce the spillover effect of having the same recruiter receiving two applications at the same time. Our concern was that, for example, having received a strong resume from the brand school, the recruiters may change their opinion on the candidate with a weak resume from a non brand school.

For the first contact, we randomly assigned the brand and resume strength for each application. For the second contact, we applied using the candidate from the 'opposite' school brand and the 'opposite' resume strength for each of the jobs we applied in Contact1.

Outcomes

Given the 2x2 design, there are several outcomes we measured in this study:

1) callbacks for brand resumes versus non-brand resumes
2) callbacks for weak versus strong resumes
3) callbacks based on the interaction between weak and strong resumes

Callbacks are defined as any follow-up from an employer, including voicemails or emails requesting an interview or requests to complete a coding test.

School Selection

On each coast we included one university that ranked stronger for engineering ("brand school") and another with a lower rank ("non-brand school").

Engineering School	Engineering Rank	In-State Tuition
UCLA	18	13,256
CSU Long Beach	137	6,524
Rutgers University	49	14,372
CUNY City College	110	6,689

Brand, Non_Brand

It was not possible to find a school with the UCLA equivalent ranking in the New York area. According to the US News World Report's rankings of engineering schools, Rutgers University was the top ranked public University in the New York/New Jersey area, coming in at #49 for all engineering schools nationwide. The only alternatives in the area were *private* schools, including Cornell University (#10), Princeton University (#11), Columbia University (#18) and Rensselaer Polytechnic Institute (#30). Rutgers University was ranked much higher than any of the SUNY Universities, and therefore was chosen for its relative strength and vicinity (recognizable in New York).

We also explored alternative states including Michigan; in this region there was no variation in school costs. Other areas were excluded for scarcity in job listings. Ultimately, the New York area was selected due to its high availability of job listings across the tri-state area.

Meet the Students

In order to avoid omitted variables related to diversity, we selected generic caucasian male names. Our four candidates included:

Jake Roberts: computer science graduate (2016) from UCLA
Jack Rogers: computer science graduate (2016) from CSU Long Beach
Jon Michaels: computer science graduate (2016) from Rutgers University
James Mason: computer science graduate (2016) from CUNY City College

Strong vs. Weak Resumes

Examples of “weak” and “strong” resumes are provided in the Appendix. Each candidate had the exact two resumes (only the names were changed). Key differences in the “strong” resume included:

- A minor in philosophy (the “weak” resume had no minor)
- Two internships versus one
- More accomplishments listed in his roles
- Honor society, Leadership activities (VP of the Association for Computing Machinery) versus hobbies (Photography Club, Radio Club)
- Overall formatting and writing was more refined
- All resumes had included the same technical skills, just in different order

Identifying Jobs

Our initial goal was to target entry level software engineering jobs for computer science students graduating in May. We realized that this would be a challenge as most established companies would have already recruited students who were about to graduate and this would impact randomization. Another issue entry level jobs in the category were in short supply.

Our final approach was to apply to positions seeking candidates with up to two years of experience. This included any available jobs for entry level Software Engineering roles.

One challenge was that some jobs were listed as “entry level” but seemed to require a significant set of skills. We had to use judgment in selecting the appropriate jobs, and agreed that fixed effects would counter any issues with over-qualification or under-qualification.

Randomization

Once we determined our candidates, their resumes and job listings, we decided to block randomize the assignments of the jobs to the candidates following a matched pair design.

We had to take the following into consideration while randomizing the assignments:

- Ensure an even split of good and weak resumes
- Ensure an even split of staggered applications
- Ensure a company gets exactly 2 resumes, one good from candidate 1 and one weak from candidate 2 with one of the two applications being staggered.

The above restrictions would allow us to evaluate responses at a company level while not raising suspicions that an experiment was being conducted. We independently randomized East and West coasts and blocked on the resume quality and the stagger covariate.

The approach we took was as follows: We created a job Id for each job opening and created two random sequences of 1's and 0's, one for resume quality and the other for stagger. For each job ID, we then assigned the resume quality and stagger ensuring none of the restrictions listed above are violated.

This randomization procedure was followed for each phase of applications we sent. In phase 1, we random assigned 40 jobs on the East Coast and 40 jobs on the west Coast and in phase 2, 30 jobs on the East coast and 40 jobs on the west coast.

Below is a summary of the final assignments.

		Phase 1		**Phase 2**	
		East Coast	**West Coast**	**East Coast**	**West Coast**
Good Resume	**Stagger**	20	20	15	20
	Not Stagger	20	20	15	20
Weak Resume	**Stagger**	20	20	15	20
	Not Stagger	20	20	15	20

Table 1: Block Random Assignments

Randomization Analysis

Given our target sample size we believed that company size would fall out naturally and therefore we did not need to provide blocking. To validate that our initial randomization worked for company size, we looked at the distribution that we randomized. For each batch of resumes (based on East vs. West Coast and Phases 1 and 2), we do see that resumes were distributed equally based on brand and non-brand. The percentage of large versus small companies does vary, however, and this is mainly due to the availability of jobs in each region and phase.

		Phase 1		Phase 2	
		Brand %	Non Brand %	Brand %	Non Brand %
East Coast	Large	14	14	18	18
	Medium	21	21	17	17
	Small	15	15	15	15
West Coast	Large	23	23	25	25
	Medium	16	16	14	14
	Small	11	11	11	11

Table 2: Percent Distribution by company size
(All values in %; cells coded with the same color add up to 100%)

Post Treatment Randomization Analysis

Once we started applying for the jobs, one challenge we faced was jobs getting closed before we applied for one or both candidates. Now since removing jobs from our analysis could potentially break the randomization we had done, we conducted a balance check to test if the difference in proportions is significant (which would indicate a need for additional weighting). For this, we analyzed the jobs where both applicants successfully applied. This filters out closed jobs and checks for any imbalance while applications were sent out (i.e imbalance in treatment assignments). We use the following model for our analysis:

$$university\_brand = 1 + good\_resume + staggered\_application$$

The results indicated no significant impact of excluding the jobs where we could not send two applications. On the East Coast we saw p-values of .46 for the staggered application and .89 for the good resume. We saw similar statistics on the West Coast. Given the lack of statistical significance, we removed the invalid job entries and continued our analysis without introducing bias in the estimates.

Soft Pilot

For this study, we could not engage in a full pilot because it would have taken too long to assess callback rates. But we did need to ensure that we could set up fake profiles on LinkedIn, and communicated closely regarding issues that came up for the initial job applications. We considered the activities a “soft pilot” rather than a formal one.

We discovered that in order to create an account on LinkedIn we needed a real phone number. This led us to create four fake virtual phone numbers that could not be tracked back to us. We also set up fake email addresses and made sure we could set up the LinkedIn accounts with those addresses.

As we applied for jobs, we identified issues where we needed to coordinate across the four team members who were applying for jobs. The issues included:

- Not applying to jobs that required a cover letter
- Making sure to indicate the candidate was a white male
- Avoiding applications requested details about current supervisor

As factors such as the exclusion of a cover letter could be considered an omitted variable, we cover these more thoroughly in the Omitted Variables section.

Two Phases

In the first phase, we applied to a total of 80 jobs, with 40 in the East Coast and 40 in the West Coast. In the second phase, we applied to 70 jobs, with 40 on the West Coast and 30 on the East Coast. Volume was based on the availability of Software Engineering roles in each area. In the second phase, we needed to expand beyond the local cities and states to identify additional jobs. The other main difference between these two phases was that we recruited LinkedIn “contacts” in phase 2 to add legitimacy to the profiles. Whether this activity helped our hurt the recruitment is unclear.

Results and Analysis

Our analysis was performed as a linear regression using OLS. The dependent variable was a binary variable where “0” represented either an explicit rejection or no contact from the company after 18 days of having sent the application. (The 18 day limit was necessary due to time constraints for the second phase of applications). For the dependent variable, a “1” represented any contact from the company about moving forward. These were either voicemails or emails left from a company representative about setting up an interview or phone call or requests to complete a coding test.

Each observation was an application sent out, but observations were only included if a company received both applications. We attempted to control for the fixed effect of each company in our model, but the model did not converge properly. We believe this may be due to an imbalance in the number of companies (105) vs. the number of applications per company (two), as well as the binary nature of our dependent variable.

Our covariate inclusion was informed by exploratory data analysis for each variable that was measured (see Appendix D: Supplementary Figures). We elected to include the coast of the application, the phase in which the application was sent out, the size of the company, and whether the application was staggered. Our primary independent variables of interest were the brand of the university and the strength of the resume.

The null hypothesis was that all universities would receive the same level of callbacks. We also hypothesized, however, that there might be an interaction between university brand and resume strength, in that the effect of a good resume matters less for those from a brand university.

Figure 1 below shows the result of the final model. Our analysis will focus on this model with the interaction term included as it was statistically significant.

Final Model

	Dependent variable:
	call_back_binary
coastWest	-0.109^{**}
	(0.039)
phasePhase2	-0.035
	(0.040)
size_binMedium	0.094^{*}
	(0.046)
size_binSmall	-0.024
	(0.045)
staggered_application	0.023
	(0.036)
university_brand	0.075
	(0.050)
good_resume	0.128^{*}
	(0.057)
university_brand:good_resume	-0.165^{*}
	(0.081)
Constant	0.058
	(0.050)
Observations	210
R^2	0.098
Adjusted R^2	0.062
Residual Std. Error	0.278 (df = 201)
F Statistic	2.735^{**} (df = 8; 201)
Note:	$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Figure 1: Final Model

Phase, stagger, and company size all had modest and statistically insignificant effects consistent with what was noticed in exploratory analysis. (Note that although the regression output shows the medium-sized companies as significantly different from the base level of large companies, significance for this multi-level factor was assessed using an F test, and the variable was found to be not statistically significant at p = .49.) The coast of applications had a highly significant effect; west coast companies had a response rate -11.1% lower than east coast companies.

The coefficients for university brand, while not statistically significant, were not consistent with our hypothesis. Brand universities got 7.5% more callbacks than non-brand universities for weak resumes, but -9.0% fewer for strong resumes (the latter estimate was produced by running the regression after flipping the binary variable representing university brand - these results are not shown in the table). However, the significance of our interaction term supports our other hypothesis. The effect of a strong resume for brand universities was not significant, but it was significant for non-brand resumes, increasing callbacks by 12.8%. The interaction term implies that the difference in the effect of a strong resume between brand and non-brand universities was 16.5%. Figure 2 below displays this interaction effect at a group level.

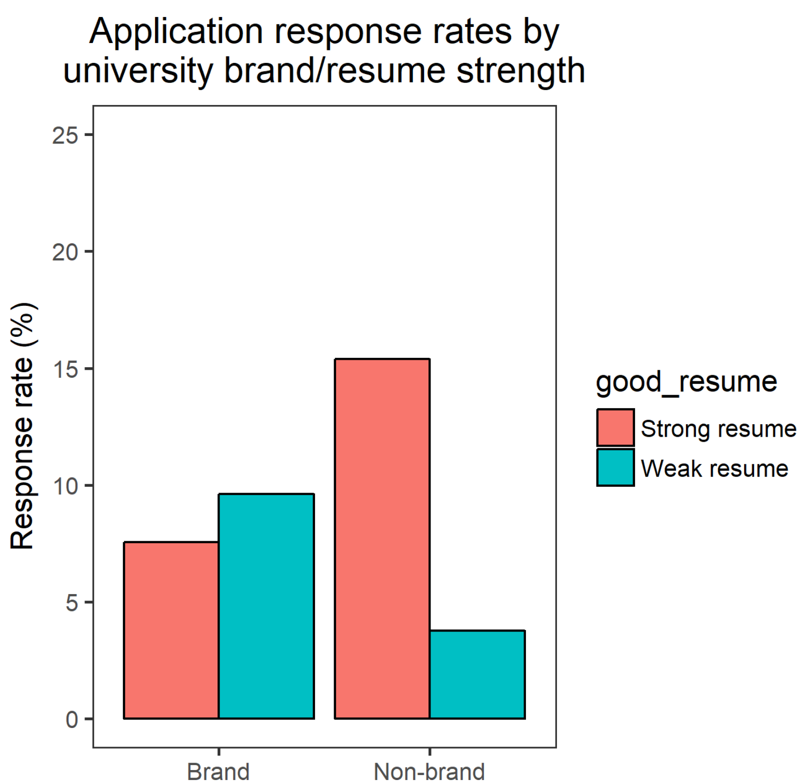


Figure 2. Response rate split by university brand and strength of resume.

Omitted Variables

We had an arguably low response rate overall and especially in phase 2 on the West coast. Could we have had better response rates had we considered additional factors? In this section we explore potential confounders we could have considered to improve response rates and potentially remove omitted variable bias.

Cover Letter

We do not know the importance of a cover letter in a job application. Since cover letters need to be customized for each job application, we decided not apply to jobs requiring a cover letter, and where it was optional, we did not add one. It’s possible that employers prefer to respond when there is a cover letter in the application and choose to ignore those that don't have one. We also recognize that failing to apply to jobs requiring a cover letter prevents us from claiming that our results can be generalized to all types of jobs. Ideally, we would have a cover letter that would be consistent yet customizable across all industries. We could not accomplish this effort given the timeframe of our project, but this would be a useful covariate to include for future studies.

Linkedin Profiles
In phase 2, we created linkedin profiles for each of our candidates to enhance believability, but even in this phase we had very few connections for each profile (<10). Because of this, we had marked each profile private and also did not include a photograph for our candidates. Moreover, to ensure only the university was visible, we didn’t add any job experience details even though the resume we had posted showed experience of nearly 2 years. This could've seemed suspicious to recruiters and may have limited the responses we received.

Applicant Tracking Systems
Many companies these days use automated tracking systems to filter out candidates based on various attributes seen in the application. Considering we used only 4 profiles, it is possible that the applicants were seen as suspicious based on filtering algorithms (unknown to us). Even though care was taken to ensure only one resume per candidate went to a specific company, its possible that related companies share resources when it comes to filtering candidates; these systems may have detected different resumes for the same candidate raising suspicions around the profiles being fake. One indicator towards this hypothesis is the response rates between phase 1 and phase 2 in the West coast. We saw a dramatic reduction in response rates in phase 2 compared to phase 1 and this is one possible explanation for this pattern. These systems may also explain lower West Coast rates, with Silicon Valley being highly likely to create and utilize such systems.

Background checks
While creating the candidate profiles we did not ensure that the names used in the profiles were actually affiliated to the universities used for the candidates. It’s possible recruiters verify student affiliations to the university as a check before responding and this could’ve affected response rates. Again, West Coast companies may have this fact checking in place for local universities such as UCLA and that may have depressed response rates for this brand school.

Resume quality
In our strong resume, we had leadership positions mentioned compared to having less serious hobbies like photography in the weak resume. Depending on the recruiter, these qualities could've been interpreted differently. For example hobbies like photography could signal a more rounded personality and recruiters could also interpret this as easier to work with. One way around this would've been to have a lot more candidates with variations in their resume making these factors even out by randomization.

Discussion and Conclusions

This study illuminates many of the complexities inherent in tracking online recruitment. While there is strong evidence that high-cost and low-cost schools would fare equally in getting notice from employers on LinkedIn, the quality of the resume appears to make more of a difference based on your school. It is possible that what we witnessed in this study is the state of this moment's algorithms. It is possible that employers (or their algorithms) seek out leadership qualities from students from lower ranked schools. But why higher ranked schools would perform lower with the leadership resume is unclear. One hypothesis is that a candidate from a very strong school such as UCLA might be more approachable with less driven resume. Or, perhaps employers have higher expectations such as as a cover letter from a brand school. Perhaps tracking systems or background checks are more firmly in place for brand schools, because employers are looking more closely at them. It is likely that one or more of these omitted variables is impacting these results.

While this study explores the relative opportunities that students from lower cost/lower ranked University might see in their applications on LinkedIn, it doesn't account for other advantages associated with attending a more prestigious school. For example, more prestigious schools may get more attention from companies during recruitment events. Attending such schools may lead to better networking and internal recommendations at desirable companies. But right now, there doesn't seem to be a bias against *leaders* from these lower ranked schools, at least not on social networking sites.

Appendix A: The Strong Resume

Jon Michaels

New York, NY | 518-801-1037 | jon.michaels64@yahoo.com

Education

Rutgers University *(August 2012 - May 2016)*
Bachelor of Arts in Computer Science with a minor in Philosophy

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Relevant Experience

Software Engineer at MayStreet, New York, NY *(June 2016 - present)*

- Built reusable and efficient front-end systems and abstractions
- Developed on-boarding experience tutorial for new users
- Worked with backend engineers and designers, to build features, ship experiments, and optimize user experience

Software Engineering Intern at Spotify, New York, NY *(June 2015 - August 2015)*

- Applied machine learning technologies to improve content quality and search functionality under the guidance of senior software engineers and architects
- Presented report on progress and development to CTO at the end of the internship

Product Development Intern at Stride, New York, NY *(June 2014 - August 2014)*

- Assisted in the development of the mobile application for Stride
- Performed quality assurance tasks and managed several large databases of user data

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Leadership/Awards

VP of Rutgers Association for Computing Machinery *(October 2014 - October 2015)*
Organized information sessions and networking opportunities for engineers at UCLA.

Rutgers Upsilon Pi Epsilon Honor Society

Technical Skills

Python, Java, JavaScript, SQL, MySQL, C, C++, Visual Studio, Visual Basic, HTML, CSS, PHP, .NET, JQuery, Backbone, J2EE, Oracle, MongoDB, Postgres, Redis, Neo4j, Hadoop, RabbitMQ, Kafka, Apache Spark, Linux, Unix, iOS, Android

Appendix B: The Weak Resume

Jon Michaels

New York, NY
518-801-1037 | jon.michaels64@yahoo.com

Education

Rutgers University
(graduated May 2016)

Bachelor of Arts in Computer Science

Work Experience

Software Engineer at Acumen Solutions, New York, NY
(June 2016 - present)

Worked with designers on projects related to user experience and new user tutorials. Primarily built and developed front-end systems.

Software Engineering Intern at NetCloud, New York, NY
(June 2015 - August 2015)

Helped to develop the mobile application for NetCloud. Wrote code and produced QA reports for senior developers.

Clubs and Associations

Rutgers Photography Club
(October 2012 - May 2016)

Rutgers Radio
(October 2015 - May 2016)

Technical Experience

Python, C, C++, Java, JavaScript, Visual Studio, Visual Basic, HTML, CSS, .NET, PHP, JQuery, Backbone, J2EE, Neo4j, Oracle, Redis, RabbitMQ, Kafka, Hadoop, Apache Spark, MongoDB, Postgres, SQL, MySQL, iOS, Android, Linux, Unix

Appendix C: Data and code reference

https://github.com/nishanth01/W241/tree/master/final_project

Appendix D: Supplemental figures

https://github.com/nishanth01/W241/tree/master/final_project/figures