Valuing the Data Economy using Machine Learning and Online Job Postings

Christopher J. Blackburn NEA Research Group March 16th, 2021



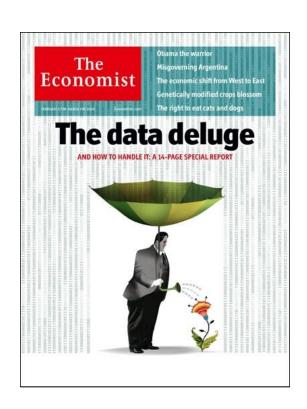
An Emerging Data Economy



The collection, analysis, and distribution of data is a hallmark of the modern economy





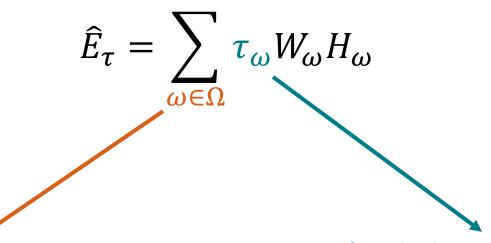


In terms of spending, how large is the data economy?

Tackling Labor Costs Estimation for Data Activities



Time-use Labor Costs Estimation



What occupations work with data?

Inclusion based on tasks performed

Ad-hoc rather than data-driven

How often do they engage with data?

Time-use factors rarely observed

50% estimate commonly assumed

We use machine learning techniques to estimate Ω and au_{ω} from online job postings

Determining Relevant Occupations



Is a job working with data? Check the job posting!

Job title: Indicates specialization, e.g., Data Engineer, Data Scientist

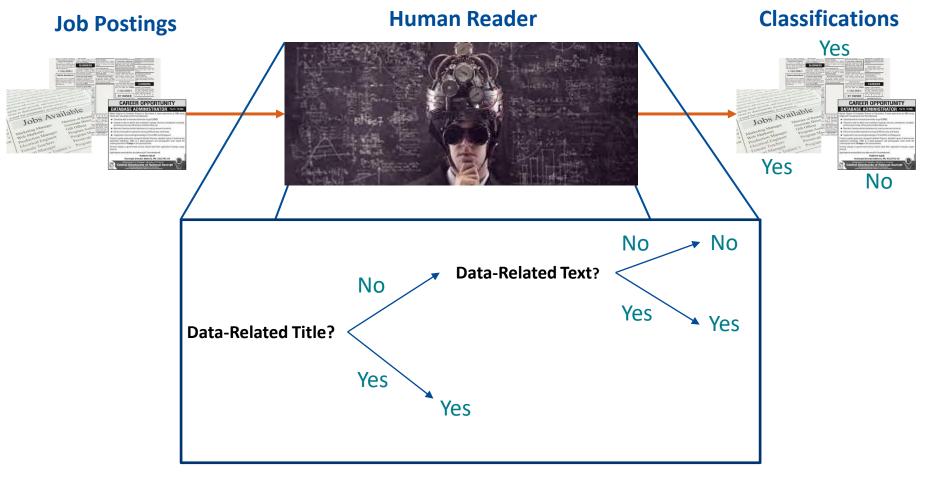


Job duties: Tasks performed, e.g., Data Analysis, Modeling

Job experience: Necessary skills, e.g., SQL, Machine learning

A (Naïve) Classification Rule





Machine Reader

Is the machine reader too naïve?



Statement 1: The data entry clerk inputs data into a database.

Data-related title: Yes Data-related text: Yes Data Classification: Yes

Statement 2: The sales representative enters customer data into a computer.

Data-related title: No Data-related text: Yes Data Classification: Yes

Statement 3: Applicant's data will not be shared with third-parties.

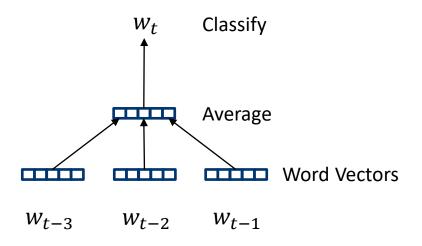
Data-related title: No Data-related text: Yes Data Classification: Yes

"Statements 1 and 2 are semantically identical, and Statement 3 is not relevant for the classification."

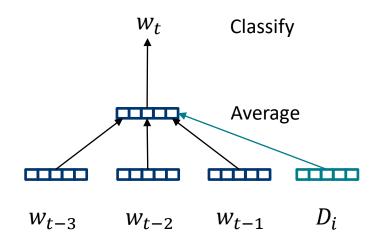
Semantic Similarity and Document Embeddings



Word2Vec (Mikolov et al. 2013)



Doc2Vec (Le and Mikolov 2014)

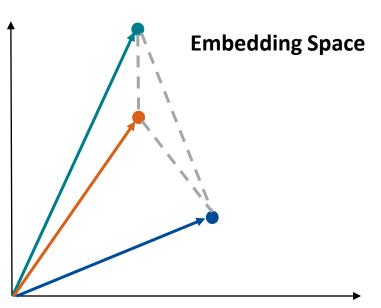




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Labor costs estimation using online job text



Online job postings from Burning Glass to estimate

$$p_{\omega}=rac{l_{\omega}}{L_{\omega}}$$
 \equiv Fraction of workers in ω engaged in data-related tasks
$$\sum_{i=1}^{L_{\omega}}\mathbb{I}\big(y_{i,\omega}=1\big)\equiv \text{Output of na\"ive dictionary-based classifier}$$

Proxy time-use using distance to "landmark" occupations

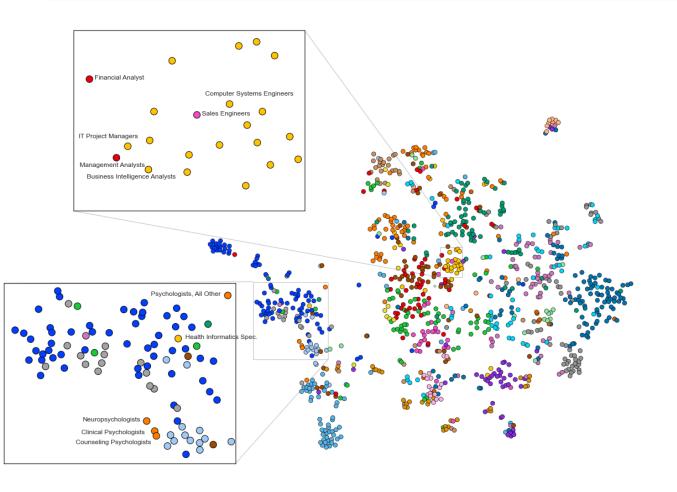
$$\tau_{\omega} = \frac{h_{\omega}/l_{\omega}}{H_{\omega}/L_{\omega}} p_{\omega} \approx \min(d_{\omega,1}, d_{\omega,2}, \dots, d_{\omega,L}) p_{\omega}$$

Construct labor costs estimates for data activities

$$E_{\tau} \approx \sum_{\omega \in \Omega} (1 - d_{\omega}^*) p_{\omega} W_{\omega} H_{\omega}$$

Landmark Occupation Vector Space (LOVeS)



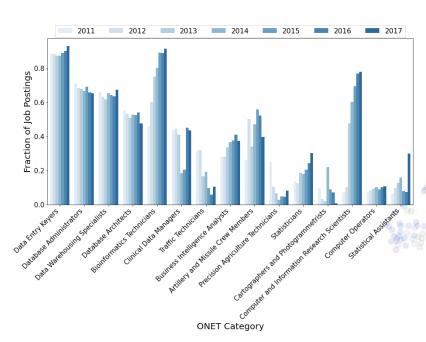


- Healthcare Practictioners and Technical
- Life, Physical, and Social Sciences
- Office and Administrative Support
- Business and Financial Operations
- Arts, Design, Entertainment, Sports, Media
- Management
- Sales and Related
- Healthcare Support
- Computer and Mathematical
- Transportation and Material Moving
- Production
- Personal Care and Service
- Architecture and Engineering
- Building and Grounds Cleaning and Maintenance
- Installation, Maintenance, and Repair
- Protective Service
- Food Preparation and Serving
- Construction and Extraction
- Legal
- Education, Training, Library
- Community and Social Services
- Military Specific
- Farming, Fishing, Forestry

Distance to Landmark "Data" Occupations



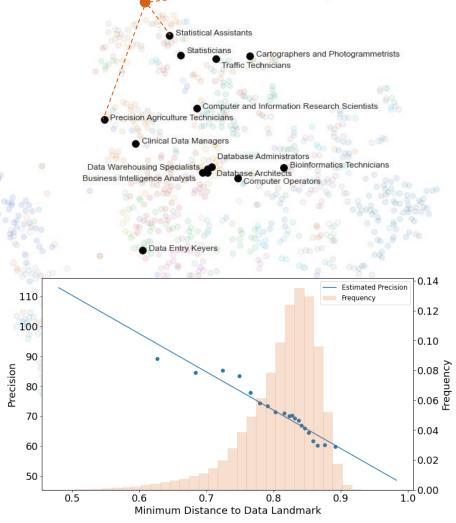
Compute minimum distance to data landmark Artillerly and Missile Crew Members



Distance function

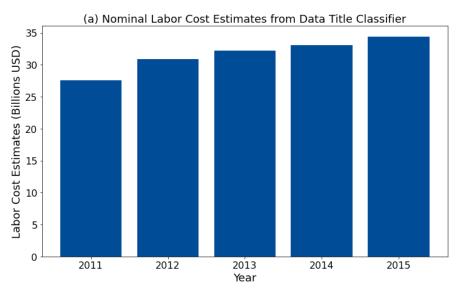
$$d_{i,d} = 1 - \cos(\theta_{i,d}) = 1 - \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|}$$

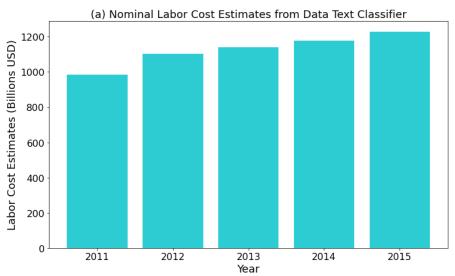
$$E_{\tau} \approx \sum_{\omega \in \Omega} \cos(\theta_{\omega}^*) p_{\omega} W_{\omega} H_{\omega}$$

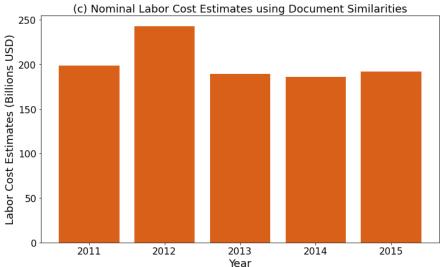


Labor Costs Estimates for Data-Related Activities









Data Title Mean Estimate: \$31 Billion

Data Text Mean Estimate: \$1.1 Trillion

Doc2Vec Mean Estimate: \$200 Billion

Conclusions and Future Work



Combine ML with online job postings to estimate labor costs of data activities

...Annual spending ranges depending on the technique

...Similarity adjusted spending estimates come in around \$200 billion annually

Future work aims to address overlap between data, R&D, and software investment

...National accounts may already capture spending on data, but how much?

Combining estimates using similar NLP techniques could yield more reliable estimate

...Many document embedding-similarity approaches exist, e.g. LDA, WMD

...Ensemble approaches usually yield more reliable estimators

Data is ubiquitous, but not nearly as exciting as popular anecdotes suggest

...Think data collected from oil changes, customer call records

...Data is everywhere, but will it show up in the productivity statistics?

Some Important Caveats



Our method assumes tasks within job postings reflect underlying composition

... Emerging tasks and responsibilities will be overrepresented

...Can potentially overestimate p_{ω} relative to true composition

Validity of our estimate relies on representativeness of job posting data

...Some occupations over/underrepresented
$$\left(\frac{L_{\omega}^{T}}{L} = \alpha_{\omega} \frac{L_{\omega}^{B}}{L}\right)$$

...Ratios might help but bias could still exist
$$\left(\frac{L_{d,\omega}^T}{L_{\omega}^T} = \frac{\beta_{d,\omega}}{\alpha_{\omega}} \frac{L_{d,\omega}^B}{L_{\omega}}\right)$$