## Data Scientists in Software Teams: State of the Art and Challenges

Original paper by: Miryung Kim, Thomas Zimmermann, Robert DeLine, Andrew Begel Summary by: Liam Day

### Introduction

Data scientists analyze data to make informed decisions regarding business and engineering.

793 professional data scientists at Microsoft were surveyed

- Some of the problems Data Scientists work on
  - User Engagement
  - Software Productivity and Quality
  - Domain Specific
  - Business Intelligence
  - Discussion

- Actual Discipline of Data Scientists
  - o 38% Data Scientists
  - o 24% Software Engineers
  - 18% Program Managers
  - o 20% Other Disciplines

# What is the demographic and educational background of data scientists at Microsoft?

- Professional Experience
  - o 13.6 Years on average
  - 7.4 Years at Microsoft
    - 9.8 Years analyzing data
- Educational Background
  - 34% Bachelors
  - 41% Masters
  - 22% PhD's

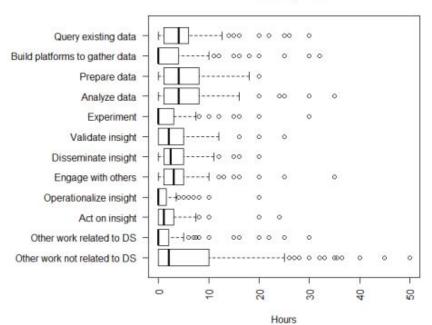
#### Skills

- Skill sets strong for things like Product
  Development, Business, and Backend
  Programming
- Structured Data, Data Manipulation, and Big Data/Distributed Systems were most frequently reported
- Spatial Statistics, Surveys/Marketing,
  Simulation, Bayesian/Monte-Carlo statistics
  were less frequently reported

## **Working Styles**

- 81%Analyze product and customer data
- 76% Communicate results and insights
- o 60% Big data cloud computing platforms
- 51% Build predictive models from the data
- 36% build data engineering platforms to collect and process data
- o 31% add instrumentation to collect data
- o 12% manage a team of data scientists

#### Time Spent



# How do data scientists work?, and what tools do they use?

- Popular tools include
  - o SQL, Excel, R, MATLAB, Minitab, SPSS, JMP, Python, Office BI, SCOPE, Azure ML, TLC
- One of the big insights of the paper was that their are too many tools.
- There are issues moving between different platforms so work has limited reusability

#### Polymath

- Jack of all trades
- Above average PHD

#### Evangelist

Explain data

#### Preparer

- Querying and manipulating data
- O Deal with many data streams

#### Shaper

- Analyzing and preparing
- Most are dedicated data scientists

#### Analyzer

Around half time analyzing

#### Platform Builder

- Building platforms and instrumentation
- Mostly software engineers

#### Moonlighter 50/20%

Less data focus

Entire population 532 people	12.0% 4.7h	7.2% 2.9h	11.7% 4.9h	12.5% 5.2h	4.8% 2.1h	6.9% 3.0h	8.5% 3.5h	9.2% 3.8h	2.4% 1.1h	5.5% 2.1h	4.1% 1.9h	15.1% 6.7h
Cluster 1 Polymath - 156 people	10.4% 4.4h	8.5% 3.6h	11.5% 5.1h	15.1% 6.7h	9.1% 4.0h	7.7% 3.6h	7.4% 3.5h	7.9% 3.6h	3.2% 1.5h	5.2% 2.3h	4.0% 2.0h	10.1% 4.5h
Cluster 2 Data Evangelist- 71 people	6.8% 2.2h	2.1% 1.0h	6.7% 2.5h	7.7% 2.9h	2.4% 1.2h	7.0% 2.6h	12.0% 4.5h	23.0% 8.6h	3.7% 1.3h	9.5% 3.3h	13.4% 6.0h	5.7% 2.6h
Cluster 3 Data Preparer- 122 people	24.5% 9.4h	4.9% 1.9h	19.6% 7.8h	10.0% 4.0h	3.0% 1.3h	9.0% 4.1h	11.6% 4.5h	8.8% 3.5h	1.5% 0.7h	3.9% 1.3h	1.5% 0.7h	1.8% 0.8h
Cluster 4 Data Shaper- 33 people	5.6% 2.5h	1.8% 0.7h	27.0% 11.5h	25.7% 10.9h	6.0% 2.6h	8.9% 3.8h	7.6% 3.3h	7.5% 3.2h	2.1% 1.0h	3.3% 1.4h	2.5% 1.1h	1.9% 0.9h
Cluster 5 Data Analyzer- 24 people	9.9% 3.7h	0.9% 0.3h	5.8% 2.4h	49.1% 18.4h	4.6% 2.2h	6.6% 2.7h	5.2% 2.2h	5.8% 2.4h	1.8% 0.9h	4.2% 1.6h	2.8% 1.3h	3.2% 1.3h
Cluster 6 Platform Builder- 27 people	12.5% 4.4h	48.5% 18.4h	6.1% 2.6h	4.3% 1.9h	3.8% 1.1h	2.7% 1.2h	4.4% 2.0h	4.1% 1.9h	2.1% 0.9h	3.0% 1.1h	1.4% 0.6h	6.9% 3.1h
Cluster 7 Moonlighter 50% - 63 people	7.3% 3.1h	5.0% 2.2h	5.0% 2.1h	5.5% 2.4h	2.8% 1.2h	4.2% 2.0h	7.8% 3.3h	5.9% 2.4h	1.8% 0.8h	5.7% 2.3h	2.5% 1.1h	46.5% 20.0h
Cluster 8 Moonlighter 20% - 32 people	2.9% 1.2h	1.4% 0.6h	1.9% 0.9h	1.6% 0.7h	0.4% 0.2h	1.5% 0.7h	1.7% 0.8h	2.3% 1.0h	0.6% 0.3h	2.1% 1.0h	2.9% 1.3h	80.9% 36.1h
Cluster 9 Insight Actor- 4 people	0.9% 0.1h	2.1% 1.0h	1.8% 0.2h		0.9% 0.1h	5.7% 1.5h	18.5% 4.8h	10.1% 1.6h	3.0% 1.1h	57.1% 11.8h		
	1	1	- 1	- 1	-	-	1			-	1	- 1

Level askilled by the contract of the state of the state

### What challenges do data scientists face?

- Data Quality
  - Limits confidence
- Data Availability
  - Missing, Incomplete, and Access
- Data Preparation
  - Format and Documentation

- Scale
  - o Time
  - Generic Tools lack feature
- Machine Learning
  - Problems are undefined
- Buy-In
  - Dedicated work is limited

# Data scientists advice to overcome those challenges?

- Better Learning
  - Things like MOOCS are currently used
- Professionalizing the practice
  - Some basis training
- Community of Practice
  - Hands on learning was a recurring request

- R was the most popular tool
- Too many tools with limited interoperability
  - Work reuse limited
- Defining and translating between goals and data
- Having a gut instinct about the data

## How do data scientists increase confidence about the correctness of their work?

- Group review
  - With peers
- Cross referencing
  - Other sources
- Human labeled ground truth
  - Need human knowledge to decide what is true
- Simulation
  - o To build up a cross reference
- Repeatability

### **Questions & Discussion**

How would you solve a too many tools issue?

### Reference

Data Scientists in Software Teams: State of the Art and Challenges

By: Miryung Kim, Thomas Zimmermann, Robert DeLine, Andrew Begel

Accessed from: <a href="http://web.cs.ucla.edu/~miryung/Publications/tse2017-datascientists.pdf">http://web.cs.ucla.edu/~miryung/Publications/tse2017-datascientists.pdf</a>

Accessed on: 2018/07/17