# Women in Machine Learning and Data Science Boston #1

March 26, 2019W

# WiMLDS Mission

WiMLDS is an international organization for women+ interested in Machine Learning and Data Science.

We host local events where we discuss machine learning and data science in an informal setting with the purpose of building a community around women and gender minorities in these fields.

# WiMLDS History

2005: Hanna Wallach, Jennifer Wortman Vaughan, Lisa Wainer and Angela Yu shared a room at NuerIPS

2006: Annual WiML Workshop begins

2013: After inspiration from WiML Workshop, Erin Ledell creates Bay Area WiMLDS meetup

2014: WiMLDS NYC created

2014: WiMLDS board created

2018: WiMLDS chapters across 6 continents

# WiMLDS Numbers

27,234 members

62 chapters

27 countries

# WiMLDS Resources

Twitter: @wimlds & @wimlds_boston

Slack: To join, email slack@wimlds.org

Job board: http://wimlds.org/jobs/

Email: boston@wimlds.org

# What should Boston be?

“The point is to show that our meetup is not only about putting women front and center, it is also a recognized scientific and technical meetup in its own right!”

- Caroline Chavier, founder of Paris WiMLDS chapter

# What should Boston be?

- How often should we meet?
- Event types:
  - Hands-on workshops
  - Speakers
  - Hack nights
  - Chapter challenges
  - Community service
  - New speaker nights
  - Panels

# Kira Tebbe

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# Stories move people.

# How do I create a story from data?

- Start with a question – then think of more questions!
- Get your data – the more the merrier!
- During data exploration:
  - Start with one of your initial questions
  - Keep an open eye for any surprises
  - Go beyond summary statistics
  - Don’t lose the forest for the trees!
- Turning results into a story:
  - Think big – what were you trying to answer?
  - Find a logical progression in your results
  - Know your audience
  - Make your slides/report/visualization easy to interpret

# Phoebe Wong

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# Phoebe Wong

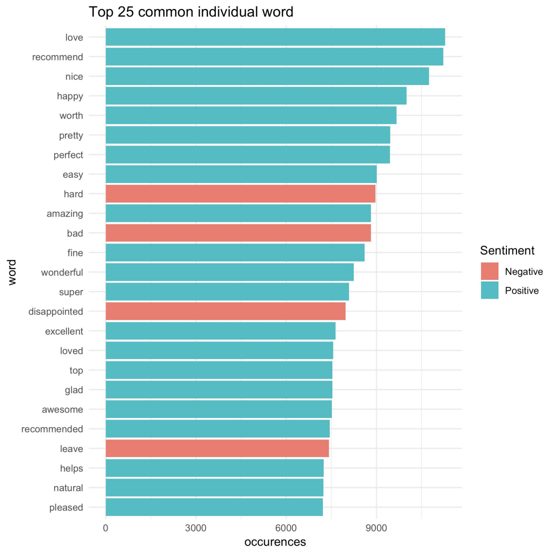
WiMLDS Boston
Mar 26, 2019

# Who am I?

- MSc in Data Science at Harvard SEAS
- Freelance Data Journalist at Fractl
- Previously, Primary Research Analyst at Legendary Pictures
- BA in Psychology from UC Berkeley

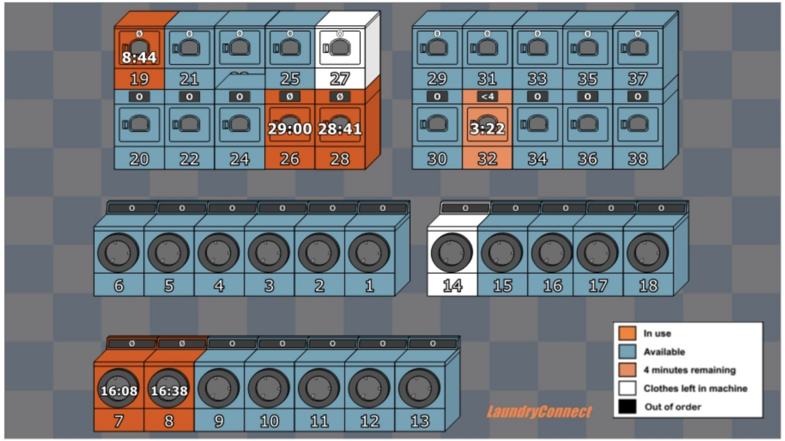
# Data Science Interest

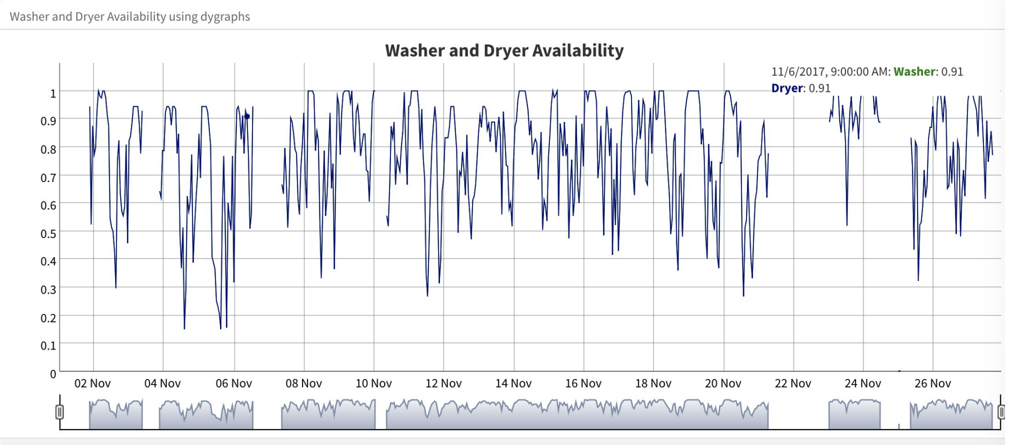
- Recommendation System
  - Song recommendation using Spotify 1 million playlist dataset
  - https://phoebewong.github.io/music-recommendation-teamNPK/
- Statistical Inferences
  - 142.8 million Amazon product rating and reviews (May 1996-July 2014)
  - https://nzstern.com/projects/amazon-product-rating-review-statistics/
- Natural Language Processing
  - Sentiment analysis of Amazon product review
- Interactive data visualization (R Shiny dashboards)



# Personal Projects

- Laundry Dashboard: https://smalldatabigfindings.com/featured-projects/laundry_flexdashboard/
- MS Outlook Meeting History Analysis: https://phoebewong.shinyapps.io/calendar_shinyio/



# R-Ladies Boston

- Co-organizer of R-Ladies Boston chapter
- Meet once every month to talk about applications of R in academia and industry
- High-level talks, hands-on workshops, project nights and social nights
    - Feb: how to build a R package, March: NLP analysis in R
- Join us on Meetup: https://meetup.com/rladies-boston/
- Follow us on Twitter: https://twitter.com/RLadiesBoston

# Love to meet you all!

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# San Wang

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# Image Forensics

WiMLDS lightning talk
3.26.2019
San Wang @ HMS

# About Me

Education

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Bachelor: Mathematics & Statistics

Master: Data Science

Data Science Journey

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ML class -> NLP research assistant -> independent projects (movie recommendation system, fashion explore platform, Kaggle)

Now

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Computer Vision Research Associate @ HMS

https://san-wang.github.io/

Now let’s talk about image forensics

# Automated Quantitative Assessment of Inappropriate Image Reuse


## San Wang
### Research Associate

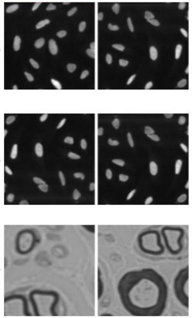
home department: **Harvard Medical School(HMS)** • supervisor: Marcelo Cicconet, Mary Walsh
research group: **HMS Office For Academic and Research Integrity(ARI) & HMS Image Data and Analysis Core(IDAC)**


## Challenges in Detection

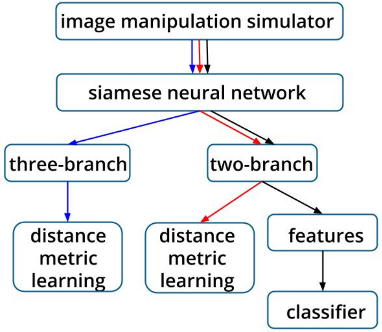
not duplication global similar

duplication with manipulation

duplication global different

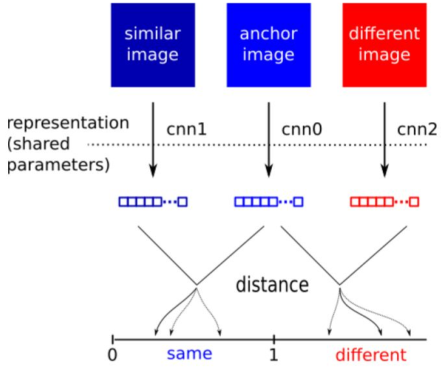


## Methods in Action

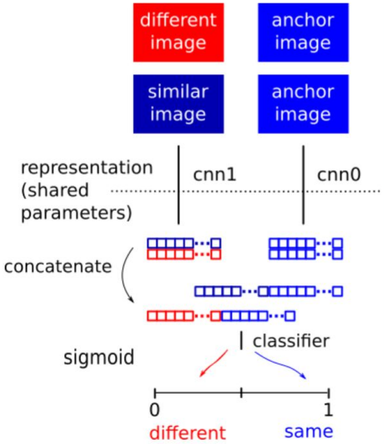



## Model Diagram Snapshot

Three-Branch Siamese




Two-Branch Siamese




cnn: Convolutional Neural Network

## Next Steps

- ➔ Combine with local image features methods
  - ◆ bag of local features
  - ◆ SIFT, SURF, edges
- ➔ Train model with cases of different complexity under hierarchical data structure
- ➔ Use attention and feature visualization to explain learned model and provide specific coordinates to indicate duplicated region
- ➔ Build manipulation verification model that can reproduce manipulation process and provide manipulation type and metric

## Result

| Model Name | Discipline | Test Accuracy |
|---|---|---|
| triplets siamese | similarity distance | 0.89 |
| twins siamese | similarity distance | 0.84 |
| | feature extraction + classification | 0.90 |

Note: test accuracy is the average of 10 runs on real world dataset using model trained on synthetic dataset, which simulates real world manipulation patterns


## Acknowledgements

Authors: San Wang[2,3], Hunter L. Elliott[2], Gretchen Brodnicki[1], Jen Ryan[1], Rachel Fouche[1], Blake Talbot[1], Daniel H. Wainstock[1], Marcelo Cicconet[2,3] and Mary C. Walsh[1,3]
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Harvard Medical School

Questions?

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# Lydia Skrabonja

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# Finding the Optimal Length of Stay in Hospice

Lydia Skrabonja
Cyft

# Cyft

- Healthcare
- Performance Improvement
- This project: end of life care

# Soft Problems

- Stigma around end of life conversations
- Many people don’t get goals concordant care

# Data Problems

- No agreed upon optimal length of stay in hospice
  - Max 6 months
- Known to save money, unknown exactly how much

# Hypothesis: For each person, there exists a cost curve along “# days in hospice” with a minima = Optimal Length of Stay in Hospice

# Proposed Solution: Step 1

- Cohort: eligible plan members who died since 1/1/2017
- Build a model that predicts Total Medical Expense (TME) in the last 6 months of life
- 1 feature = % of last 6 months enrolled in hospice
- Current step

# Proposed Solution: Step 2

- For each member
- For all values of “% of last 6 months enrolled in hospice”

- Generate the expected TME in the last 6 months
- Find the minima/inflection point/etc
- Output the difference in both # days and TME

# Proposed Solution: Expected Outcomes

- Overall
    - Savings of the current hospice program
    - How aligned the hospice program is timing-wise

- Individually
    - Optimal length of stay for each member
    - Expected cost for no hospice
    - Expected savings with optimal hospice

# Thank you!

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# Sarah Rich

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# Making Great Private Recommendations

**Sarah Rich** (@sarahjrich)
**Machine Learning at Canopy** (@ourcanopy)

# How Do “We” “Usually” Do ML For Personalization?

- Log everything (geo-tracking, in-app behavior, in-app history, device IDs, browser history, co-occurring app installs)
- Store everything (write pipelines to parse this data and make it readily accessible at scale)
- Train models on all of this data to predict interest/engagement/demographics
- Use this data for analytics and advertising:
  - Who do we think is using our product and how can we improve it based on that information?
  - Who do we think is using our product and how can we sell their attention to advertisers?
- (Maybe even?) Sell this data

# What's Wrong With This Picture?

- Possible data breaches leave sensitive data vulnerable
- The app is not the product; the person using the app is the product
- The customer is advertisers or data brokers
- Fundamental mismatch between what we're doing and what we say we're doing
- Feels disingenuous and erodes trust between the person using the app and the company

# What We’re Doing Instead at Canopy

- Content recommendation (articles and podcasts right now)
- Want to know as little about you as possible
- Store zero raw data on our servers
- Train an ML model online that is differentially private
- We are focused on making private recommendations as delightful as possible

# What This Means for Me

- Analytics: have to be private and online, suitably aggregated
- Training ML models: We don’t store any raw training data!
- Getting to solve super interesting new problems and help build a better Internet!

# Thank you!

@sarahjrich @ourcanopy

1. What was the last movie you saw?
2. What was the most frustrating bug you worked on lately?
3. Share a shocking statistic.
4. Favorite place to eat in Boston?
5. What is something cool you have programmed lately?
6. Where were you living in 2012?