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Criss-Crossing the Org Chart
Predicting Colleague Interactions with R

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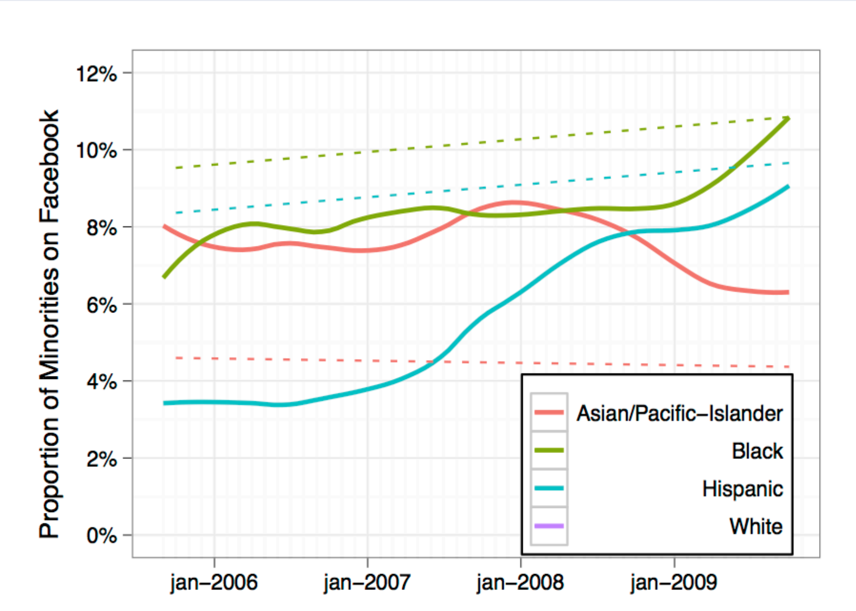
Introduction: How Facebook uses R

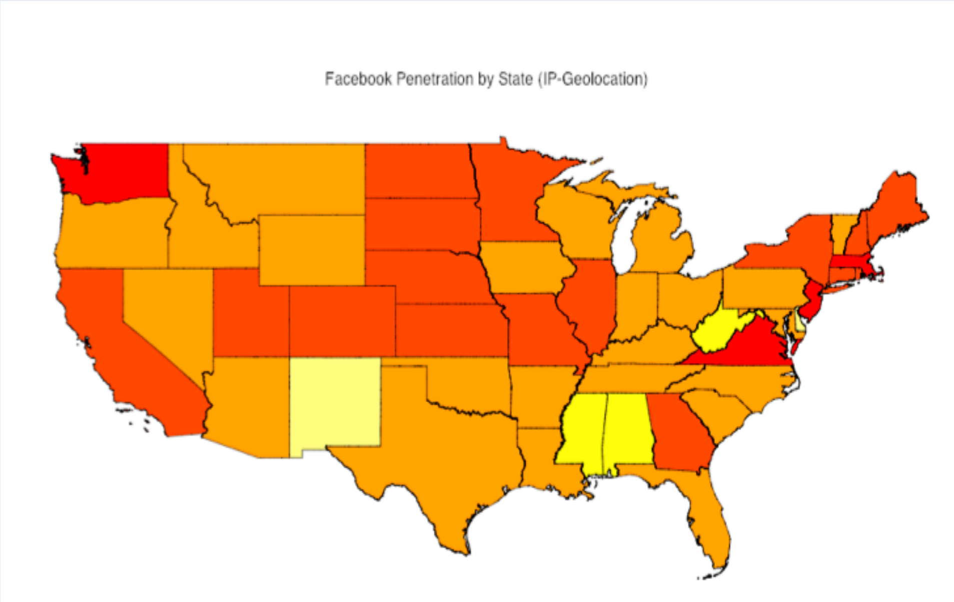
- Experimentation for large machine learning models
  - Picking models
  - Feature selection
- Small/medium one-off analyses
  - user engagement studies
  - analyses to improve internal processes

How Facebook uses R (cont.)

- Analysis and visualization for social networks research



from Chang, et al. (ICWSM 2009)



from Backstrom, et al. (WWW 2010)

- Facebook Data Team: http://www.facebook.com/data

Predicting Colleague Interactions

Potential Applications

- Suggesting peer reviewers during performance review season
- Setting up optimally-constructed teams within a company
- Optimizing seating charts for maximum productivity
- Automatically filtering internal feeds of employee content (such as commit logs) to deliver personalized content to each employee
- Suggesting new colleague interactions (based on second-degree connections) that may be useful to one's work
- Giving managers more insight into their employees' interactions

Goals

- Attempt to predict the total # of colleague interactions in the next 4 weeks across all internal tools
- Provide an API for other engineers to use in their internal tools, and publish a daily dashboard to show each employee their current results

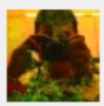
Pipeline Overview

Employee Interaction Data (MySQL) → Raw CSV → MySQL Storage → Front-End Dashboard and API

Final Results

- Daily cron job: R predictions -> RMySQL -> web page dashboard

Eric Sun's Predicted Colleague Interactions

		User	Score
1		Alexander Strehl	9.3318008583172
2		Aaron Binbin Liao	8.1162385345038
3		Srinivas Narayanan	3.2938821239025
4		Jack Zhao	3.0129828038274
5		Austin Haugen	2.4928669082428

Predictors

- Direct communication metrics
  - # code reviews requested
  - # mailing list threads shared
  - # shared threads on internal task management tool
  - # shared threads on internal message boards
- Implicit interaction
  - # meetings co-attended
- Org chart dummy variables (manager, report, peer)

Feature Generation

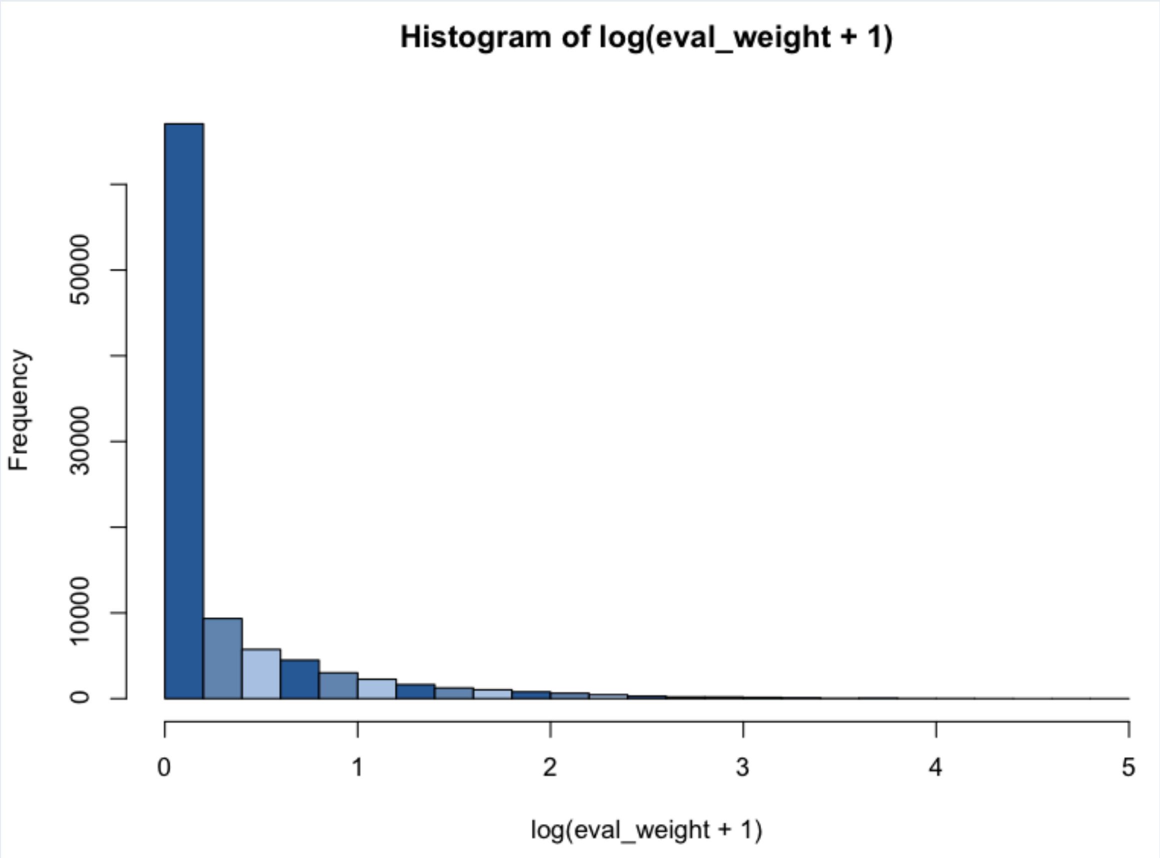
- For each set, use Cartesian product to generate pairs of interactions
- All features weighted by 1 / (# participants – 1)
- Example:
  - Alice, Bob, and Charlie attend a meeting.
  - Generate A->B, A->C, B->A, B->C, C->A, C->B with weight 0.5 for the 'meeting' variable, then aggregate across IDs and type

The Data

```
> crisscross.data <- read.csv('crisscross_training_data.csv')

> nrow(crisscross.data) # low-weight observations filtered out

[1] 98802
```

```
> crisscross.data[sample(nrow(crisscross.data), 5), ]

     id1       id2 meeting mailinglists codereviews  tasks messageboards imageshare manager peer report eval_weight
<hidden> <hidden>  0.0000            1           0 1.2834         0.000          0       0    0      0      0.0000
<hidden> <hidden>  1.7833            0           0 0.0000         0.000          0       0    0      0      0.0000
<hidden> <hidden>  0.0041            0           0 0.2000         0.000          0       0    0      0      0.0039
<hidden> <hidden>  0.0000            0           0 0.0000         0.125          0       0    0      0      0.0000
<hidden> <hidden>  0.0000            0           0 0.1250         0.000          0       0    0      0      1.8744
```

Long Tail of Interactions



Machine Learning

- All subsequent stats computed on a single Linux machine
- Dual-core 2 Mhz server, 16GB RAM
- Tried a variety of techniques: linear regression, random forests, boosted trees, etc.
- Used standard 2/3 – 1/3 split for training and test data

```
> nrow(full_data)
[1] 98802   # ~50 per employee
> nrow(test_data)
[1] 32934
> nrow(train_data)
[1] 65868
```

Linear Regression

```
> system.time(crisscross.lm <- lm(eval_weight ~ ., data = train_data))
   user  system elapsed 
  0.866   0.106   0.973 
> summary(crisscross.lm)

Call:
lm(formula = eval_weight ~ ., data = train_data)

Residuals:
      Min        1Q    Median        3Q       Max 
-38.31223  -0.28494  -0.15137   0.02445  57.11911 

Coefficients:
               Estimate Std. Error t value Pr(>|t|)    
(Intercept)   -0.071232   0.009224  -7.723 1.16e-14 ***
meeting        0.572376   0.024526  23.338  < 2e-16 ***
mailinglists   0.257495   0.009799  26.278  < 2e-16 ***
codereviews    0.693076   0.005563 124.598  < 2e-16 ***
tasks          0.890425   0.004206 211.704  < 2e-16 ***
messageboards  0.767063   0.063873  12.009  < 2e-16 ***
imageshare     0.810893   0.152074   5.332 9.73e-08 ***
manager        0.488565   0.046915  10.414  < 2e-16 ***
peer           0.255186   0.017801  14.336  < 2e-16 ***
report         0.483349   0.047139  10.254  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.878 on 65858 degrees of freedom
Multiple R-squared: 0.5451,     Adjusted R-squared: 0.5451 
F-statistic:  8770 on 9 and 65858 DF,  p-value: < 2.2e-16
```

Random Forests

```
> require(randomForest)
Loading required package: randomForest
randomForest 4.5-30
Type rfNews() to see new features/changes/bug fixes.
> reg_x <- train_data[, -which(names(train_data) == 'eval_weight')]
> system.time(crisscross.rf <- randomForest(x = reg_x, y = train_data$eval_weight))
   user  system elapsed
631.132 180.815 812.141
> summary(crisscross.rf)
                Length Class  Mode
call                3  -none- call
type                1  -none- character
predicted       65868  -none- numeric
mse               500  -none- numeric
rsq               500  -none- numeric
oob.times       65868  -none- numeric
importance          9  -none- numeric
importanceSD        0  -none- NULL
localImportance     0  -none- NULL
proximity           0  -none- NULL
ntree               1  -none- numeric
mtry                1  -none- numeric
forest             11  -none- list
coefs               0  -none- NULL
y               65868  -none- numeric
test                0  -none- NULL
inbag               0  -none- NULL
```

Boosted Trees

```
> require(gbm)
Loading required package: gbm
Loading required package: survival
Loading required package: splines
Loading required package: lattice
Loaded gbm 1.6-3
> system.time(crisscross.gbm <- gbm(eval_weight ~ ., data = train_data,
+ n.trees = 1000, cv.folds = 5, distribution = 'laplace',
+ interaction.depth = 2))
   user  system elapsed
270.108   0.594 270.810
> summary(crisscross.gbm)
            var     rel.inf
1         tasks 84.97515128
2       meeting 15.00431911
3          peer  0.02052960
4  mailinglists  0.00000000
5   codereviews  0.00000000
6 messageboards  0.00000000
7    imageshare  0.00000000
8       manager  0.00000000
9        report  0.00000000
```

Comparison of Techniques

- Use held-out test set to evaluate results

	Linear Regression	Random Forests	Boosted Trees
Running Time (seconds)	0.973	812.141	270.81
Sum of Squared Errors	111,188.59	**60,316.21**	226,923.10
Mean Squared Error	3.74	**2.03**	7.64
Median Squared Error	0.09	0.05	**0.01**
Quantiles of Squared Errors:			
0%	**0.00**	**0.00**	**0.00**
20%	0.01	0.02	**0.00**
40%	0.04	0.03	**0.00**
60%	0.11	0.08	**0.02**
80%	0.55	0.35	**0.28**
100%	5,829.69	**2,644.87**	13,713.43

Summary & Future Work

- Remarkably simple, automatic pipeline delivers useful insight into organizational behavior
- Pipeline integrates R seamlessly with data stored in databases
- Many useful applications for internal tools

- To do: integrate into applications mentioned previously
- To do: explore visualization techniques with R graphics!

- These slides are posted at http://www.stanford.edu/~esun/

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