Analyzing User Behavior at *PlentyOfFish:* Data Science in the Wild

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My background

- Started life as a string theorist and cosmologist
  - PhD from UPenn (2006)
  - Postdoc at NYU (2006-2009)
  - Postdoc at UBC (2009-2012)
  - 19 papers and ~600 citations in topics spanning black hole physics, particle physics and Big Bang cosmology
- Currently a Data Scientist at PlentyofFish

My current company: PlentyofFish

- World's largest online dating site: 3.3 million users log in per day, 55 million registered users
- In 10 years grown from a one man operation to ~75 employees
- Web and native apps for iPhone, iPad and Android
- 5 man research team with PhDs (and one BS) in physics, CS, and machine learning
- Work with CUDA clusters, R clusters, ...

Outline of talk

- The data
  - What does the raw data look like?
  - Can we process the data for fast reads for this problem?
- Data wrangling
  - Even processed we can't really learn or analyze
  - How can we summarize the data?

Outline (part 2)

- Data Wrangling (optimizing or welcome to the cluster!)
  - Can we do this in parallel?
  - Building out a distributed cluster for analytics in R
    - doRedis
    - Custom package development
- Feature and data exploration
  - Exploratory CART trees for feature selection
  - Regression techniques
  - CART trees for user insights
- Conclusions and questions

The problem (the data)

- PoF is currently building out its own real time analytics platform
- Part of that is recording user pagehits on the site which allows for much deeper analysis than Google analytics
- The raw data is simply stored as a postgresql table like so

eventid	userid	eventtime	pagehit
1050	56	1370555569	inbox.aspx
1051	23	1370555571	homepage.aspx

The problem (the data)

- Now imagine we want to get entire tracks, grouped by user:
  - *select userid, eventtime, pagehit from raw.data where userid in (56,...) order by userid asc, eventtime asc;*

eventid	userid	eventtime	pagehit
1050	56	1370555569	inbox.aspx
1051	23	1370555571	homepage.aspx
...			
2032	56	1370555623	matches.aspx

- This filter is *O(N)*, the sort is *O(m log m)* (where m elements are left after the filter)
- This is slow for millions of rows, and we have billions. Is there a faster way?

The solution (data)

- What if we can eliminate the filter... and the sort?
- Let's look at how the data is structured:
  - Right now it's by eventid/time
  - What we want is something indexed and ordered by userid, ideally with as few rows/user as possible
  - What can we do with Postgresql to accomplish this?

The processed table
(with a lot of help from Nisan Haramati)

- Enter: Native arrays in Postgresql
- We can store the events in a time series array, new events are simply appended as they arrive
- This leaves a table with one array per dimension, per user, and a single row per user

  select userid, dataarray from array.table where userid in (56,...)

- This is *O(1)* to choose a row, add elements and read the array (no complex filter, no sort because data is stored contiguously and in order on the file system)

Bonuses

- We can slice arrays
- We can get metadata such as length, histogram of array elements...
- Significantly more efficient in memory and storage
- Native set operations

Data Wrangling

- Ok, so we can get data out at a reasonable clip now (later on we'll do even better)
- The data still isn't really in the form we can really play with and start learning on, so what can we do?
- A few options:
  - We can try and keep the entire path and do some form of graph analysis: the downside to this is that there's a lot of pages and the paths quickly get exponentially complicated. Not a good call for an initial foray
  - We could try and summarize the data in a nice way and work off the summary/aggregates: This is a good first step

Data Wrangling

- The obvious (to me) is to summarize by counts/page or counts/pagetype
- We also may want to only look at the first session, first x hours, or break up by idle time periods → write a routine to handle all these and spit out required data only
- Take into account the distribution of a user session spent on each part of the site (e.g. 13% on their inbox) and total time spent on the site in the period
- Finally, there's lots of other metadata such as messaging, demographic information etc. contained in a separate MSSQL database. We need to pull this in too.

More data wrangling

- I used R for this (including direct database extraction)
- Packages used:
  - RpostgreSQL, RODBC, reshape2, plyr, foreach, sampling...
- My code for a set of users:
  - Opens up connections to SQL and PostgreSQL
  - Pulls metadata and usertracks per user from SQL and the polarized table
  - Finds the first session or x hours
  - Processes and aggregates the data
  - Returns a summarized data frame like

userid	inbox	matches	perc_inbox	...	Messages sent	Total Time
25	13	5	0.23		6	456

Parallel Computing (enter the cluster)

- So far, all the computations and even queries we've done are by user, there are no interactions
- This can be done in an embarrassingly parallel fashion → We can use a cluster
- There are lots of options in R for parallel computation (see the CRAN taskview on high performance computing)
- We wanted something that satisfied:
  - Easy and generic to write code for many tasks → fast development time and quick iteration
  - Mature and supported
  - Fault tolerant
  - Scales
  - Nodes can be heterogeneous

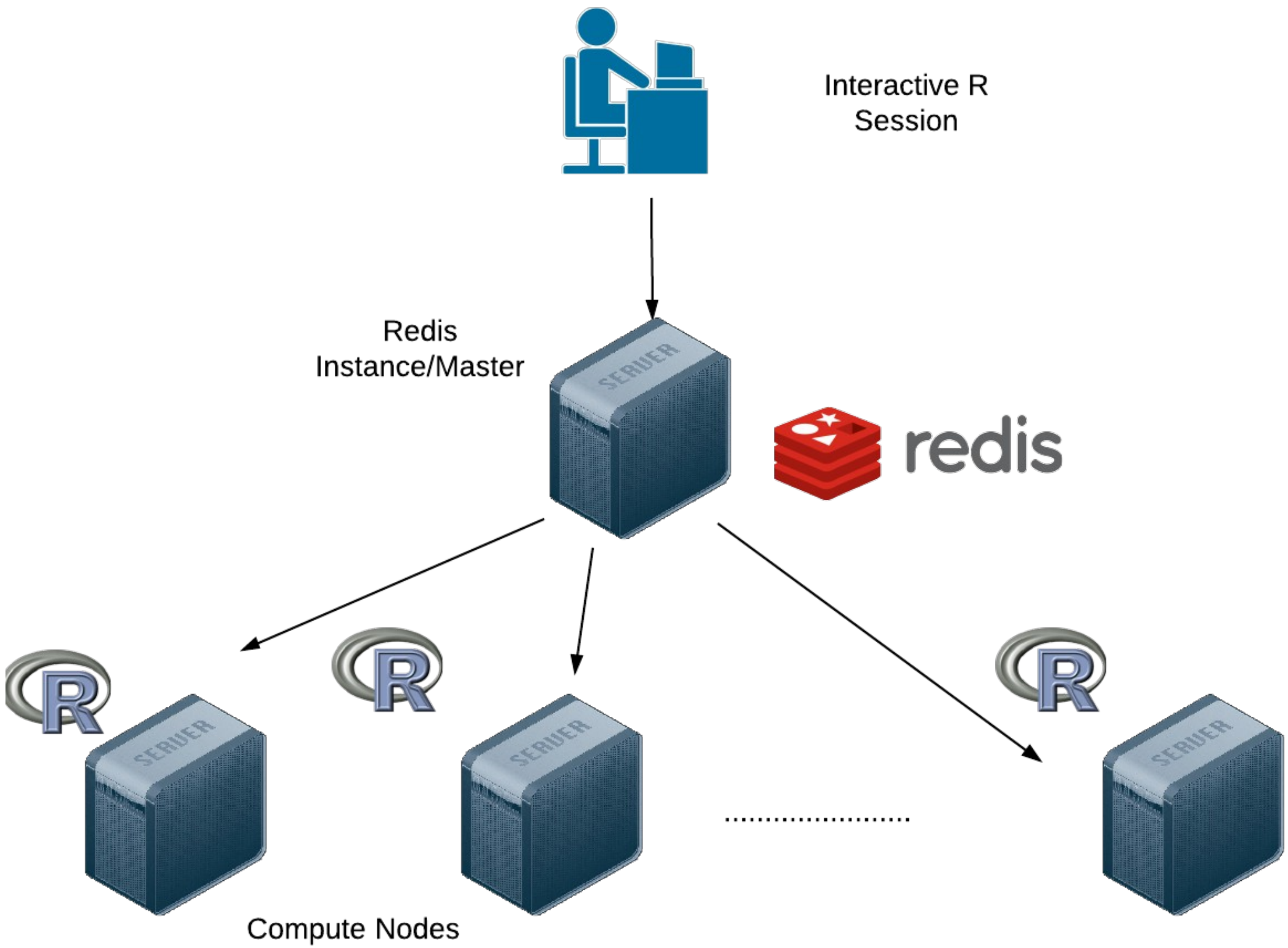
R Cluster

- The packages *foreach* and *iterators* allow for a generic and “simple” programming model → Not much different than writing a loop, except you specify how to iterate (map), process and combine (reduce)
- You can do most anything in the loops you want, even things like database calls
- *foreach* requires a *parallel backend* to be registered, otherwise it will operate sequentially. There are a lot of options here from utilizing multiple cores on your local machine, SOCK clusters, etc.
- The *foreach* code works with any backend → no rewriting

R Cluster (the parallel backend)

- *rredis* and *doRedis* provide a very good option for a parallel backend
- *doRedis* uses a Redis server as a job queue, it is
    - Fault tolerant
    - Allows for heterogeneous nodes
    - Allows for spawning nodes *during* a computation

Cluster Architecture
(with a lot of help from Nisan Haramati)



Cluster design

- *doRedis* is an excellent package, but we needed some additional functionality on the nodes:
  - DB connectivity functions
  - The ability to spawn nodes, connect to queues and flush memory from bash scripts or from the client side
  - Administrative functionality
  - Integration across multiple servers
  - Code deployment via SVN
- This led to me developing two custom packages (and several scripts and settings files):
  - *databaseConnections* (extends *RODBC* and *RpostgresSQL*)
  - *redisCluster* (extends *rredis* and *doRedis*)

Challenges for *redisCluster*

- Very early on in development, basic functionality
- Features that would be great to add:
  - Ability to spawn nodes remotely from within a client R session
  - Better control and ability to flush memory on queues
  - Redis has a hard limit of 512 MB for strings → doRedis can choke with larger sets at times. Would be great to have a way to chunk up the message string to start the jobs and return the data
  - A robust job manager
  - a la Hadoop → Ability to store data on nodes so it doesn't have to be passed

Upshot for data wrangling

- We've gone from a large single query on the raw table to many cluster based queries on a polarized, structured table and optimized aggregating/wrangling
- All of these changes reduced the timing exponentially. A rough number is on about 50K users' tracks (~50 million events) we reduced the timing from several hours to roughly 90 seconds!

Other (awesome) things you can do with this

- Rapidly iterate through many machine learning algorithms and parameter spaces (e.g. *caret* automatically uses *foreach*) with minimal dev time (literally changing a line or two of code and iterate on large sets quickly), e.g.
    - Neural nets
    - Random forests
    - A variety of boosted models
    - Bayesian models
    - C5.0
    - ...
- Able to process on terabytes of data
- Can rapidly explore and orthogonalize large parameter spaces
- ….

(Almost) done wrangling

- We're just about there, *except* we need to look at outliers
- There are small pockets of users who have either way more/less total and individual page hits over a given time period
  - Plot a histogram or distribution of these things, look for long tails on either end
  - This in fact gives an easy to implement routine in R for excluding them
    1) take attributes you want to eliminate outliers on
    2) Build a histogram
    3) Take any users that are in the very long tails and put them in the outlier set → left with a more normalized population
- This is a bit of an open question, include or not? I chose to do both and performed analysis on the whole set, the normalized population and sometimes just the outliers

(Almost, almost) done wrangling

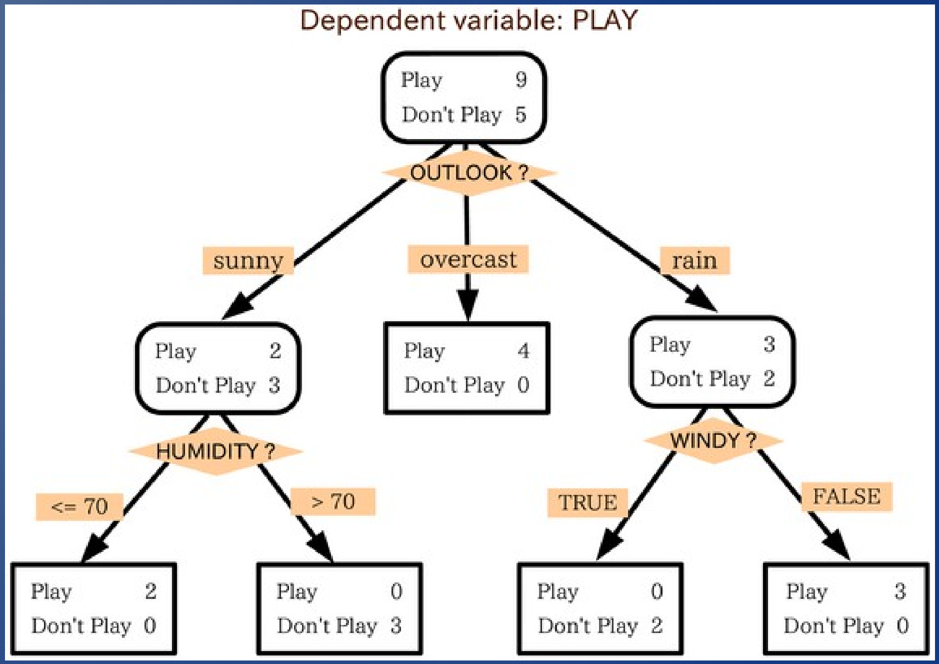
- Lastly, there are some holes in the data itself when the system was down or not recording properly. We can filter these out in two ways:
  - Look at first eventtime and compare to known creation time (in other DB)
  - Look at density of events overall, and filter around holes

Data Exploration

- Whew! Finally have data we can iterate quickly on and into a reasonable form
- Lots of things we can do with it:
  - Examine various averages and distributions
  - Build classifiers
    - We could go the highly accurate route (e.g. SVMs, neural nets, random forests etc.)
    - At this stage though, we're more interested in *what* are the important events and features our users experience → regression, trees etc., i.e. models that are easily interpretable

CART Trees

- In our case we want to predict whether or not a user will have deleted their profile at some time in the future based on their initial actions
- Use the trees to explore which features are most important for a given subset of users (e.g. m/f)
- I mostly used *rpart*
- What splits give the highest information gain
- What subset of attributes are most predictive?
- Test, prune, feature select, test, prune, feature select,...



Regressions

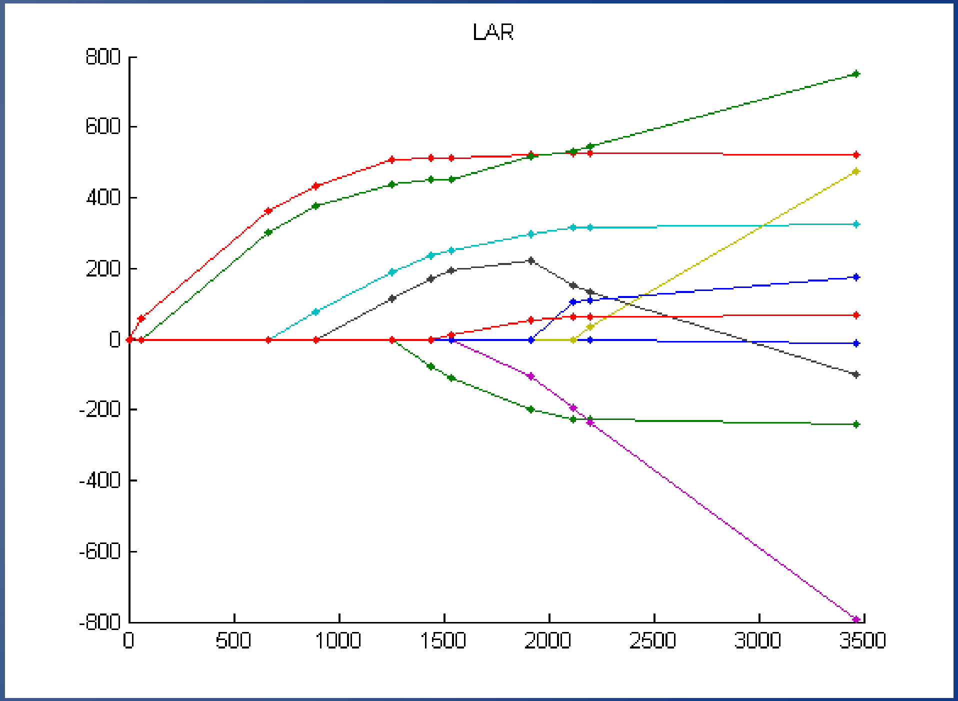
- We can use the information from the trees to start filtering out variables, which are most important?
- For example, some analysis showed that the more time users spend online in their first day, the more likely they are to become engaged and happy (not exactly earth shattering)
- We can then examine which other attributes are good predictors of that using a linear regression or stepwise routine like LARS

LARS (Least Angle Regression)

- Lars is form of linear regression
- We are trying to predict a result *y* with the formula

$$\hat{y} = \beta_0 + \beta_1 x^1 + \ldots$$

- We do this stepwise, at each step we choose the predictor most correlated with *y*
- Increase the new β in the direction of its correlation with *y*.
- Move in equiangular direction until another variable is as correlated
- Continue till all predictors are in the model



- This gives a series of steps that rank attributes in order of importance so we can see what the best predictors are

~~Results~~

- This... I can't actually tell you, you'll just have to come work with me if you want to hear about it

Wrapup

- I (hope) I've shown you what it's like to be a Data Scientist at POF for a couple of weeks
- As you can see, this project involves many steps, calls that have to be made and diverse skillset and tools → That's pretty much being a Data Scientist
- This is one project, some others I've been involved in:
  - Scam detection
  - Bot detection
  - Matching algorithm
  - Lexical processing
  - …
- If you want to chat more: Add me on LinkedIn or Twitter: @tslevi
- Thanks for listening! (now let's go get a beer)