ML for the industry
Part 1

MLSS 2016 – Cádiz

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Criteo

Why such a class?

- Companies are an ever growing opportunity for ML researchers
- Academics know about the publications of these companies
- ...but not about the less academically-visible research

A new zoology of problems

- Most academic literature is about predictive performance

- What about:
  - Optimisation of decision-making?
  - Increasing operational efficiency?
  - Predictive performance under operational constraints?

The 3 stages of the academia → industry move

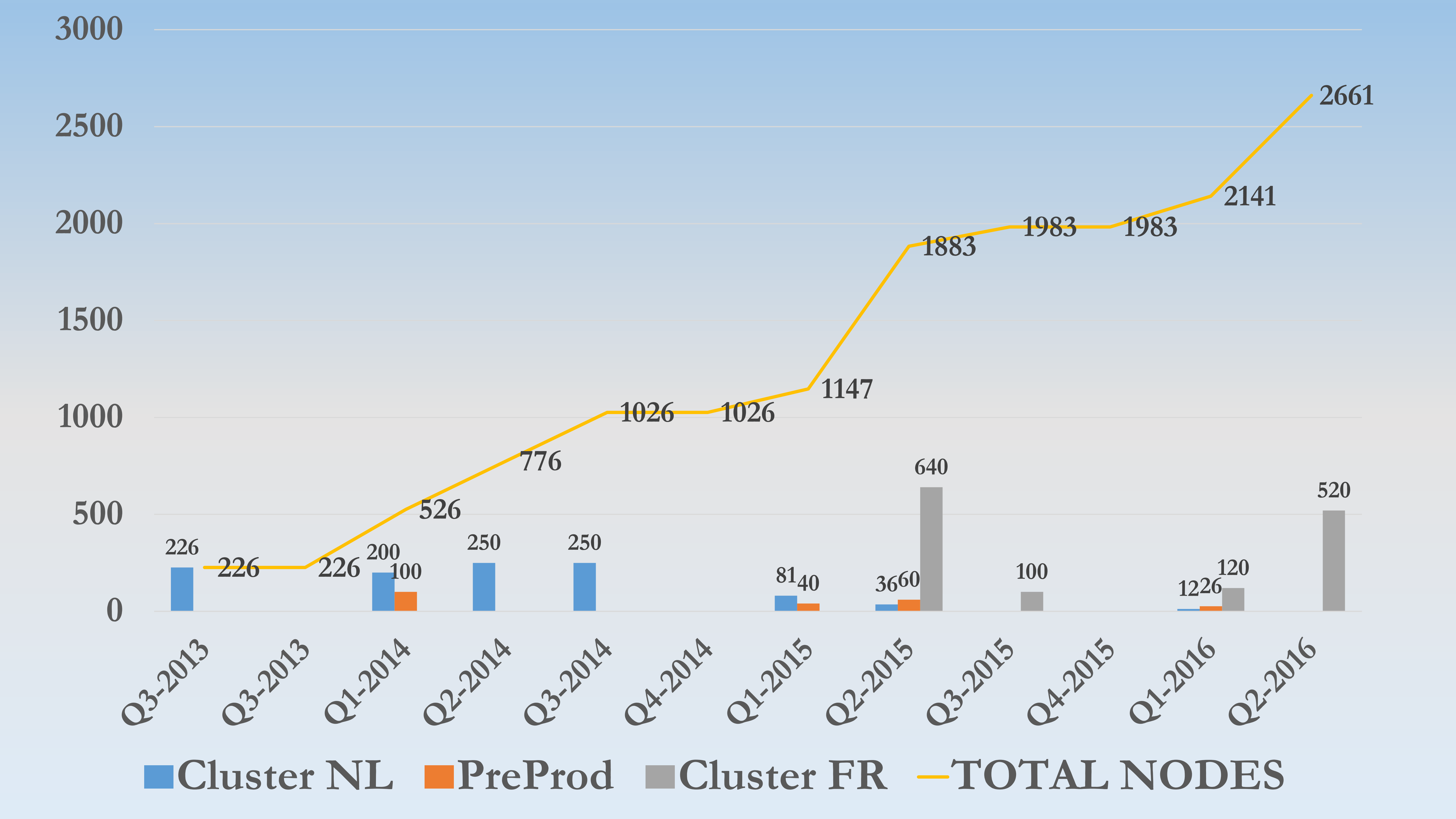
1. I will use model X which will greatly improve the results (enthusiasm)

2. No new model is useful, this is pointless (disillusionment)

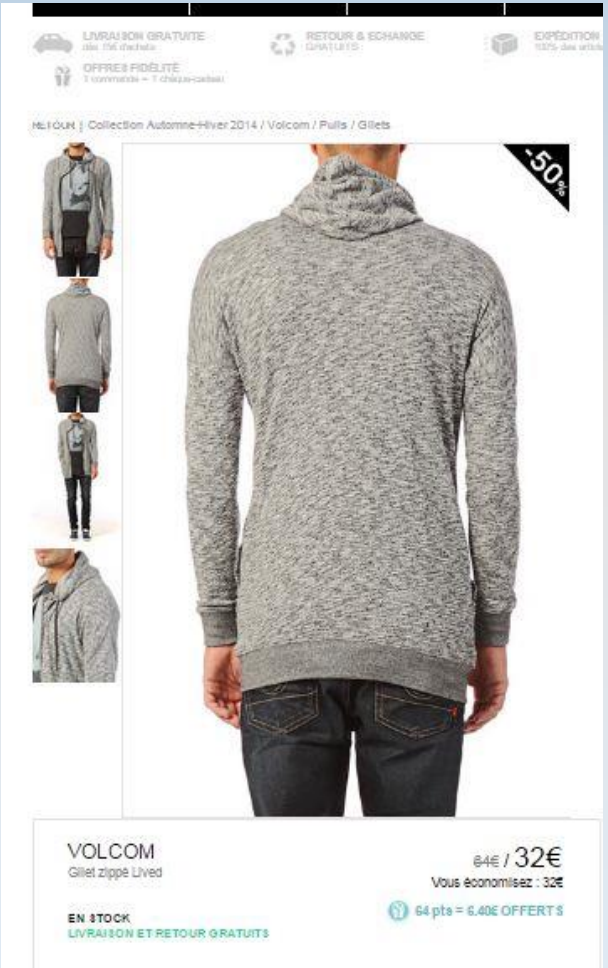
3. So many open questions, I do not know where to start (acceptance)

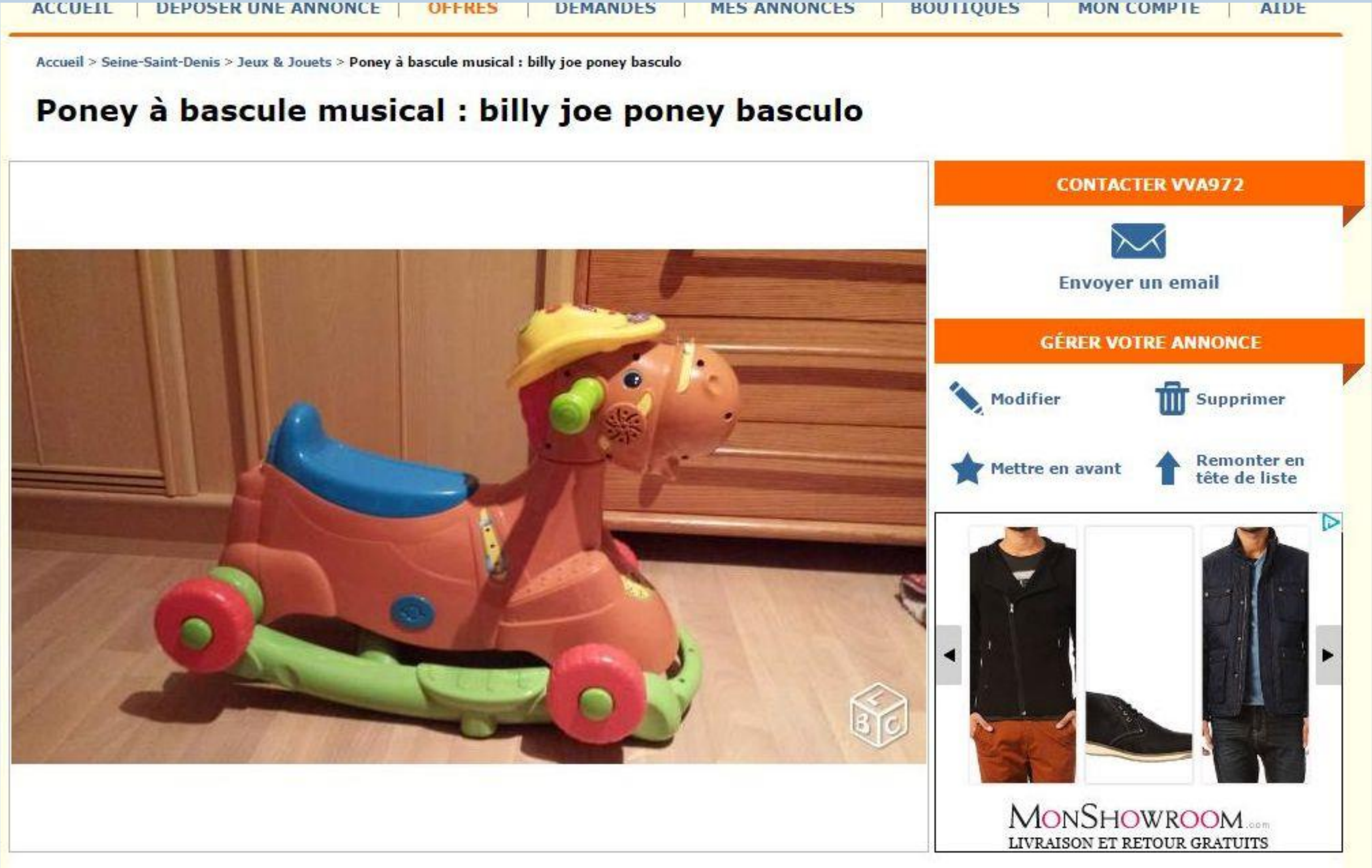
Criteo – an example amongst many

- We buy advertising spaces on websites
- We display ads for our partners
- We get paid if the user clicks on the ad


3000
2500
2000
1500
1000
500
0
226
226
226
200
100
526
250
776
250
1026
1026
81
40
1147
36
60
640
1883
100
1983
1983
12
26
120
2141
520
2661
Q3-2013
Q3-2013
Q1-2014
Q2-2014
Q3-2014
Q4-2014
Q1-2015
Q2-2015
Q3-2015
Q4-2015
Q1-2016
Q2-2016
Cluster NL
PreProd
Cluster FR
TOTAL NODES

Retargeting – an example





In practice

1. A user lands on a webpage
2. The website Criteo and its competitors
3. It is an auction: each competitor tells how much it bids
4. The highest bidder wins the right to display an ad

Details of the auction

- Real-time bidding (RTB)
- Second-price auction: the winner pays the second highest price
- Optimal strategy: bid the expected gain
- Expected gain = price per click (CPC) * probability of click (CTR)

What to do once we win the display?

- We are now directly in contact with the website
- Choose the best products
- Choose the color, the font and the layout

Identified ML problems

- Prediction problem: click/no click
- Recommendation problem: find the top products

What is the input?

- The list of data we can collect about the user and the context
- Time since last visit, current URL, etc.
- There is potentially no limit to the number of variables in X

Choosing a model class

- Response time is critical
- There is little signal to predict clicks: we need to add features often
- Solution: a logistic regression - pCTR = $\sigma(w^T x)$

A major difference

Structured data

- Lots of info in the data
- High predictability
- Highly structured info

Hierarchical models

Unstructured data

- Poor predictability
- Signal dominated by noise
- Highly unstructured info

Linear models

Dealing with many modalities

- Some variables can take many different values
  - CurrentURL
  - List of articles read
  - List of items seen

Idea 1: one-hot encoding + dictionary

- Associate each entry with an index i

- x = [0 0 0 ... 0 1 0 ... 0 0]

  0 1 2 i (P-2) (P-1)

Idea 1: one-hot encoding + dictionary

- Associate each entry with an index i

- x = [0 0 0 ... 0 1 0 ... 0 0]

  0 1 2 i (P-2) (P-1)

- pCTR = $\sigma(w^T x) = \sigma(w_i)$

Building a dictionary

i	URL	w_i
0	http://google.com	-1.2
1	http://facebook.com	-3.4
…		
…		
129547171991	http://thiswebsiteisgreat.com	-0.5

Building a dictionary

i	URL	w_i
0	http://google.com	-1.2
1	http://facebook.com	-3.4
…		
…		
129547171991	http://thiswebsiteisgreat.com	-0.5
129547171992	http://thisoneisevenbetter.com	-0.45

Idea 2: using a hash table

i	w_i
0	-1.7
1	-2.1
…	
…	
…	
16777215	-1.2

- h: $S \rightarrow [0, 2^k - 1]$
- h("http://google.com")=14563

Idea 2: using a hash table

i	w_i
0	-1.7
1	-2.1
…	
14563	-1.23
…	
16777215	-1.2

- h: $S \rightarrow [0, 2^k - 1]$
- h("http://google.com")=14563

Collisions

- What if $\mathrm{h}(S_0) = \mathrm{h}(S_1)$?
- We will use the same $\mathrm{w_i}$ for both.
- This is called a collision.

Collisions in practice

- h("http://google.com") = h("http://nicolas.le-roux.name")=14563
- pCTR("http://google.com")= pCTR("http://nicolas.le-roux.name")

    ≈ CTR("http://google.com")

Example of a hash

- Current URL = http://gobernie.com/

- $h(\text{"http://gobernie.com/"}) = 12$

- $x = [0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0]$

  0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15

Example of a hash

- Current URL = http://gobernie.com/ and Advertiser = S&W
- h("http://gobernie.com/") = 12 , h(" S&W ") = 4
- $x = [0\ 0\ 0\ 0\ {\color{red}1}\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ {\color{red}1}\ 0\ 0\ 0]$

  0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15

Limitations of the linear model

- $x = [0\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0]$

- pCTR = $\sigma(w^T x) = \frac{1}{1 + e^{-w^T x}} \approx e^{w^T x} = \prod_i e^{w_i x_i}$

Introducing cross-features

- Current URL = http://gobernie.com/ and Advertiser = S&W
- $h(\text{"http://gobernie.com/" and " S\&W "}) = 6$
- $x^{cf} = [0\ 0\ 0\ 0\ 1\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0]$

  0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15

Cross-features as a second-order method

- $x = \quad [0\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0]$
- $x^{cf} = [0\ 0\ 0\ 0\ 1\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0]$

Cross-features as a second-order method

- $x = \quad [0\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0]$

- $x^{cf} = [0\ 0\ 0\ 0\ 1\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0]$

- $w^T x_{cf} = \sum_i \ w_i x_i$

Cross-features as a second-order method

- $x = \quad [0\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0]$

- $x^{cf} = [0\ 0\ 0\ 0\ 1\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0]$

- $w^T x_{cf} = \sum_i \; w_i x_i + \sum_{i,j} w_{ij} x_i x_j$

Cross-features as a second-order method

- $w^T x_{cf} = \sum_i w_i x_i + \sum_{i,j} w_{ij} x_i x_j$

- $w^T x_{cf} = w^T x + x^T M x$

The values in M are the same as those in w!

A matrix view of cross-features

- pCTR = $\sigma(x^T M x)$

M=

2.3	1.1	3.7	-3.0	1.1	2.3
-1.4	2.3	-3.0	3.7	-1.4	3.7
-3.0	-3.0	5.9	1.1	2.3	5.9
3.7	5.9	-1.4	1.1	-3.0	-1.4
-1.4	2.3	-1.4	-1.4	3.7	5.9
-3.0	1.1	1.1	5.9	5.9	5.9

The structure is determined by the hashing function

Exploiting the magic

"Thanks to hashing, the number of parameters in the model is independent of the number of variables. This means we should add as many variables as possible."

Reasons to NOT do that

- Because of collisions, adding variables may decrease performance

- Any variable needs to be computed and stored

The cost of adding variables

- *« Hey, I thought of this great variable: Time since last product view. Can we add it to the model? »*
- Storage: #Banners/day x #Days x 4 = 480GB
- RAM: #Users x #Campaigns x 4 = 40GB

Feature selection

- How to keep features while maintaining good performance?A tool to increase statistical efficiency
- Solution: selection of the optimal features and cross-features

Using sparsity-inducing regularizers

- $\min_{w} \sum_i \; l(w, x_i, y_i)$

Using sparsity-inducing regularizers

- $\min_{w} \sum_i \; l(w, x_i, y_i) + \; \lambda \|w\|_1$
- Statistically efficient
- Still requires to extract all variables

Using group-sparsity regularizers

- $\min_{w} \sum_i \; l(w, x_i, y_i) + \; \lambda \sum_{g} \|w_{g}\|_2$

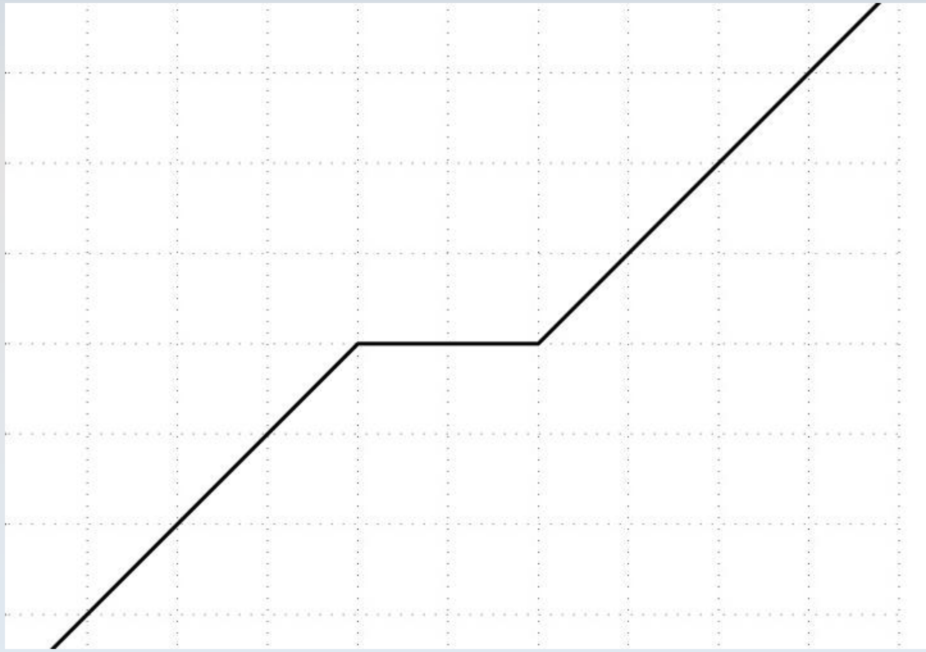
- Forces all elements in a group to be 0

- The optimization problem remains efficient

R. Jenatton, J.-Y. Audibert and F. Bach. Structured Variable Selection with Sparsity-Inducing Norms. *Journal of Machine Learning Research*

Reducing bias

- Sparsity-inducing regularization introduces bias
- Two-stage process:
    - Select subset of variables
    - Re-optimize with the selected subset



Feature selection as kernel selection

- $w^T x_{cf} = w^T x + \ x^T M x$

- Doing feature selection on M is equivalent to learning the kernel

ML improves human efficiency

- Adding features is a critical part of an R&D
- Doing it automatically and well spares valuable people's time

Factorization machines

- pCTR = $\sigma(x^T M x)$

M=

2.3	1.1
-1.4	2.3
-3.0	-3.0
3.7	5.9
-1.4	2.3
-3.0	1.1

2.3	-1.4	-3.0	3.7	-1.4	-3.0
1.1	2.3	-3.0	5.9	2.3	1.1

Rendle, S. Factorization machines. In *Data Mining (ICDM), 2010 IEEE 10th International Conference on* (pp. 995-1000). IEEE.

Factorization machines

- $\phi(w, x) = w^T x$
- $\phi(M, x) = x^T M x$
- $\phi(U, x) = x^T U U^T x$

Linear model

	gobernie.com	drumpf4ever.com	hillaryous.com
S&W	$f(w_{bernie} + w_{S\&W})$	$f(w_{drumpf} + w_{S\&W})$	$f(w_{hillary} + w_{S\&W})$
Carebear	$f(w_{bernie} + w_{carebear})$	$f(w_{drumpf} + w_{carebear})$	$f(w_{hillary} + w_{carebear})$
JP Morgan	$f(w_{bernie} + w_{JPMorgan})$	$f(w_{drumpf} + w_{JPMorgan})$	$f(w_{hillary} + w_{JPMorgan})$

Level 2 cross-features

	gobernie.com	drumpf4ever.com	hillaryous.com
S&W	$f(w_{bernie,S\&W})$	$f(w_{drumpf,S\&W})$	$f(w_{hillary,S\&W})$
Carebear	$f(w_{bernie,carebear})$	$f(w_{drumpf,carebear})$	$f(w_{hillary,carebear})$
JP Morgan	$f(w_{bernie,JPMorgan})$	$f(w_{drumpf,JPMorgan})$	$f(w_{hillary,JPMorgan})$

Factorization machines

	gobernie.com	drumpf4ever.com	hillaryous.com
S&W	$\mathrm{f}(\boldsymbol{w}_{bernie} \cdot \boldsymbol{w}_{S\&W})$	$\mathrm{f}(\boldsymbol{w}_{drumpf} \cdot \boldsymbol{w}_{S\&W})$	$\mathrm{f}(\boldsymbol{w}_{hillary} \cdot \boldsymbol{w}_{S\&W})$
Carebear	$\mathrm{f}(\boldsymbol{w}_{bernie} \cdot \boldsymbol{w}_{carebear})$	$\mathrm{f}(\boldsymbol{w}_{drumpf} \cdot \boldsymbol{w}_{carebear})$	$\mathrm{f}(\boldsymbol{w}_{hillary} \cdot \boldsymbol{w}_{carebear})$
JP Morgan	$\mathrm{f}(\boldsymbol{w}_{bernie} \cdot \boldsymbol{w}_{JPMorgan})$	$\mathrm{f}(\boldsymbol{w}_{drumpf} \cdot \boldsymbol{w}_{JPMorgan})$	$\mathrm{f}(\boldsymbol{w}_{hillary} \cdot \boldsymbol{w}_{JPMorgan})$

A side-by-side comparison

Standard cross-features

2.3	1.1	3.7	-3.0	1.1	2.3
-1.4	2.3	-3.0	3.7	-1.4	3.7
-3.0	-3.0	5.9	1.1	2.3	5.9
3.7	5.9	-1.4	1.1	-3.0	-1.4
-1.4	2.3	-1.4	-1.4	3.7	5.9
-3.0	1.1	1.1	5.9	5.9	5.9

- Frequent values are unregularized
- Infrequent modalities have random weights

Standard cross-features

2.3	1.1
-1.4	2.3
-3.0	-3.0
3.7	5.9
-1.4	2.3
-3.0	1.1

2.3	-1.4	-3.0	3.7	-1.4	-3.0
1.1	2.3	-3.0	5.9	2.3	1.1

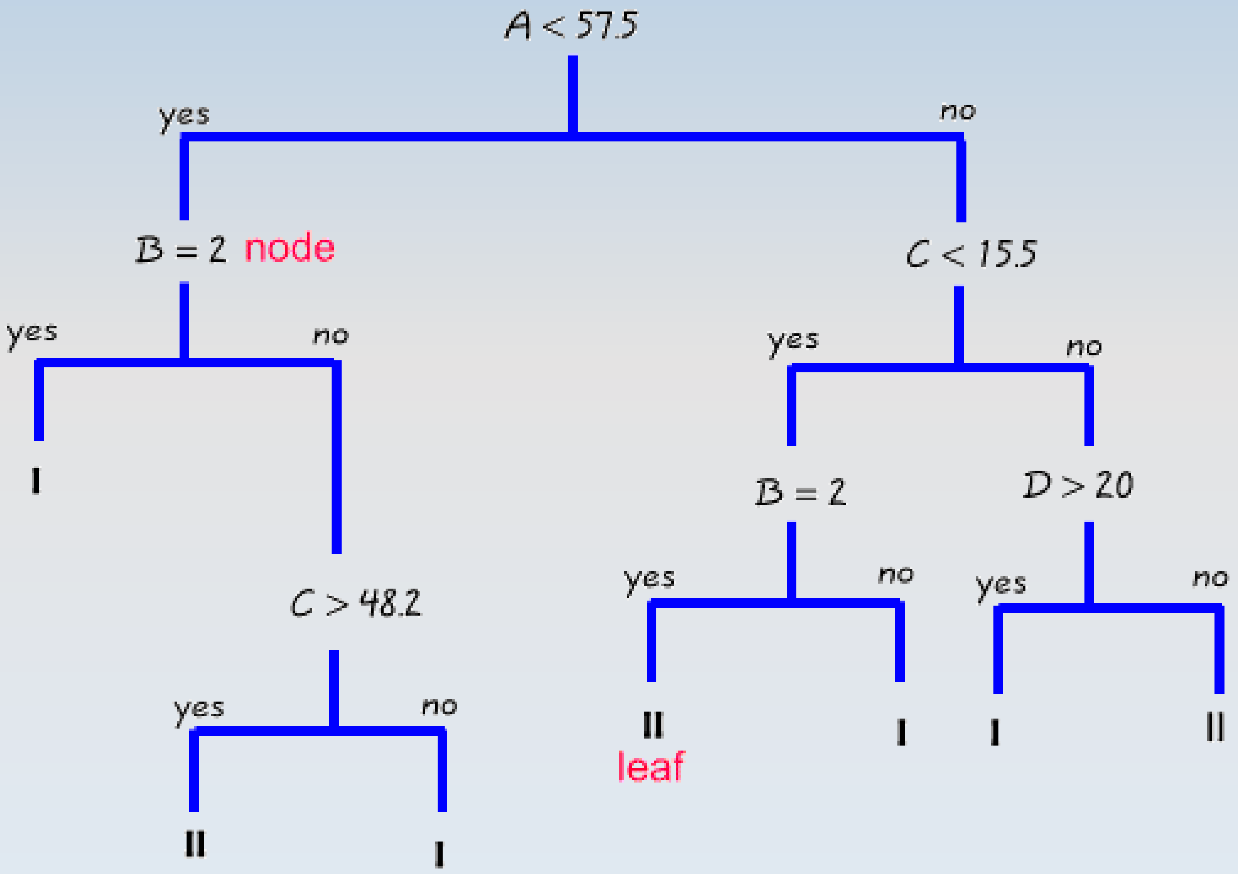
- All values are regularized

Handling continuous features

- Using a continuous feature directly only allows for linear interactions
- Finding the optimal transformation can be cumbersome

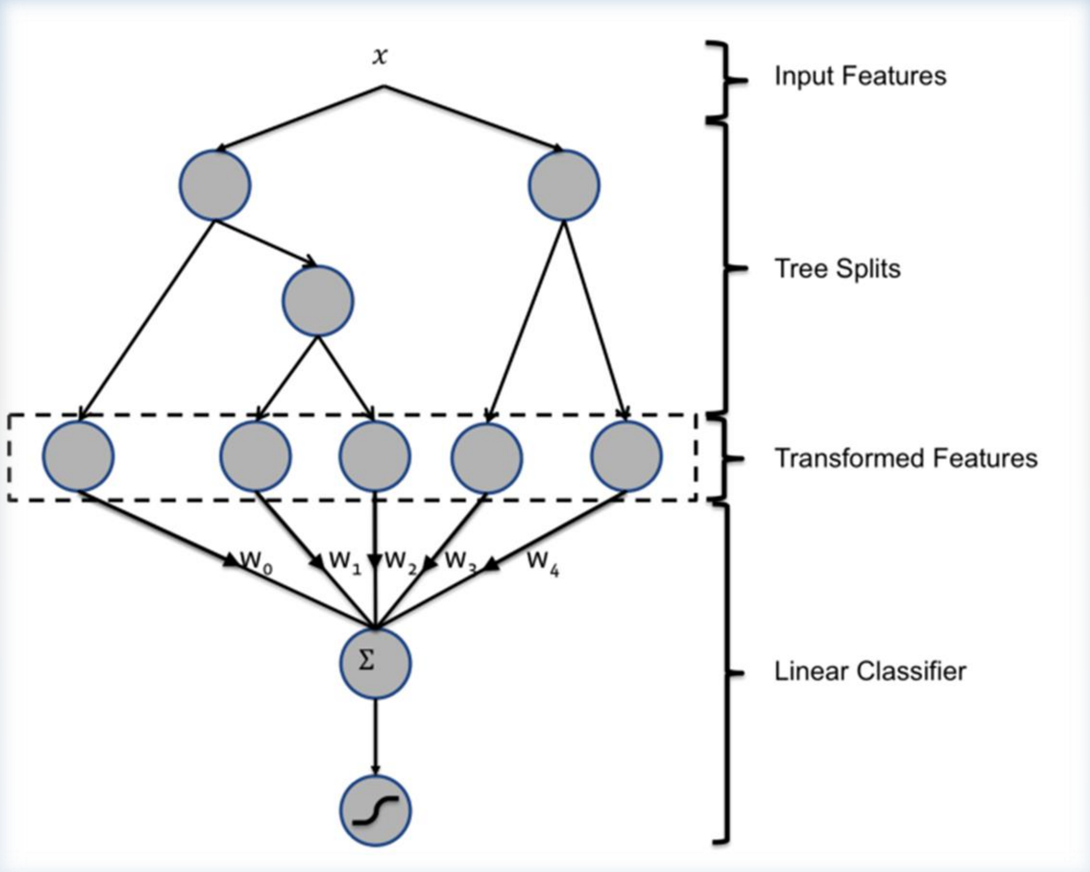
Gradient boosted decision trees

- Learn a decision tree to predict the clicks
- Learn a forest using boosting



Incorporating GBDT into a linear classifier

- Use the index of the leaves as categorical features



He et al. Practical Lessons from Predicting Clicks on Ads at Facebook. ADKDD

Learning the parameters

- $n = 10^9$, $p = 10^8$
- Theory tells us that stochastic gradient methods should be used

Arising optimization questions

- How do you set the stepsize for each of the 40 models?
- Does it change when we add features?
- How do you distribute the optimizer?
- Do all the datapoints have equal value?

Comparing the costs

- ML researcher: above 100k€ / year
- 16 CPUs - 64GB RAM: 5k€
- Win a factor 2 in 2 weeks

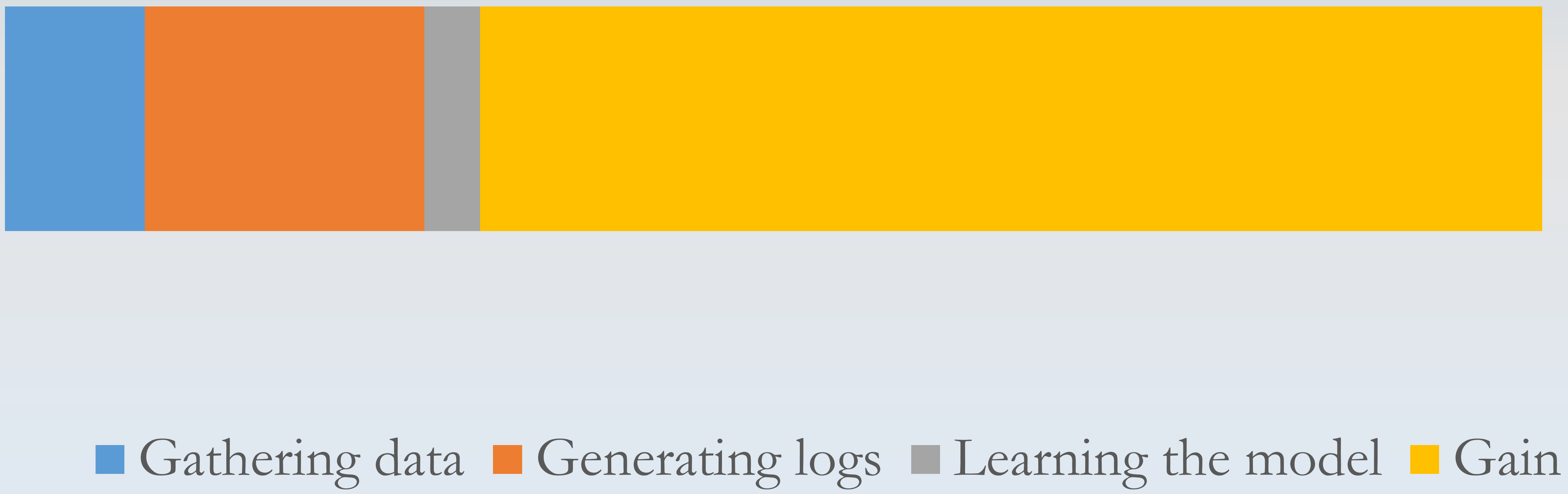
Further complications

- Increasing learning speed reduces delay
- But we still need to wait for the data
- And also for the log generation
- Learning time on a single machine at Criteo: 24 hours

A view of the entire pipeline

A view of the entire pipeline

A view of the entire pipeline



Focusing on the right problem

- After a bit, the return is too small
- It is important to identify when and to focus on other aspects
- Remember that what matters is the whole system

Comparison of optimization methods

<u>Stochastic methods</u>

- $O(1/T)$ convergence rate
- Cost independent of N
- "Faster" early on
- $O(1/T)$ on the test error

<u>Batch methods</u>

- $O(\rho^T)$ convergence rate
- Cost linear in N
- "Faster" later on
- $O(1/T)$ on the test error

Real comparison of optimization methods

<u>Stochastic methods</u>

- Careful with the stepsize!
- Hire a team to distribute it
- "Faster" early on

<u>Batch methods</u>

- Line-search and forget
- 10 lines of code to distribute
- Initialize properly

Robustness trumps accuracy

Criteo's optimizer

- Distributed L-BFGS
- Distributed computation of the gradients (10^7 examples/s)
- Update computation on a single node

Automatic hyperparameter optimization

- Number of hyperparameters grows w/ complexity of the model
- Optimizing them efficiently can have a huge impact
- Current approaches use GPs to model the test error as a function of their values

Noisy targets

- So far, we focused on a click prediction model
- It is probably not what we want
- The true goal is the (incremental) sale

Predicting sales

- There are far fewer sales than clicks (1 sale for 10 000 displays)
- They come after 30 days

Approximating 30-day sales

- We can use sales over a shorter period
- This leads to biased prediction
- What else can we do?

Modeling delayed feedback

- E = elapsed time since the click
- D = delay between the click and the sale
- Y = did the sale already occur?
- C = will a sale eventually occur?
- Build a joint model P(C, D)

Modeling delayed feedback

- P(C): probability that a sale will occur
- P(D|C=1): probability of observing a delay D for occurring sales
- If Y=0 after elapsed time E, then

$$P(C=1 \mid Y=0, E) = \int_{D>E} P(C = 1, D) dD$$

Chapelle, O. Modeling delayed feedback in display advertising. KDD

From unsupervised to weakly supervised learning

- Unsupervised learning tries to learn about the input data
- Weakly supervised learning uses related tasks
  - Long visits on the website
  - Sales which do not follow a click
- Big data: unstructured targets rather than inputs

Michaeli et al. Semi-supervised single- and multi-domain regression with multi-domain training. Information and Inference