SPARK+AI
SUMMIT EUROPE

Using Deep Learning in Production Pipelines
to Predict Consumers' Interest

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#SAISML2

Who am I ?

Mathieu DESPRIEE

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In charge of ML Scalability & Operability

Contributor to Spark, MxNET

TINYCLUES IN A FEW WORDS

AI-FIRST
SAAS SOLUTION

DEEP LEARNING FOR CAMPAIGN
TARGETING & PLANNING

ACROSS ALL
CHANNELS

DRIVE MORE REVENUE
AND ENGAGEMENT

DESIGNED FOR
MARKETERS

USING ANONYMIZED
FIRST PARTY DATA

SEAMLESSLY INTEGRATED WITH
YOUR MARKETING STACK

FIRST CAMPAIGNS IN
2 WEEKS

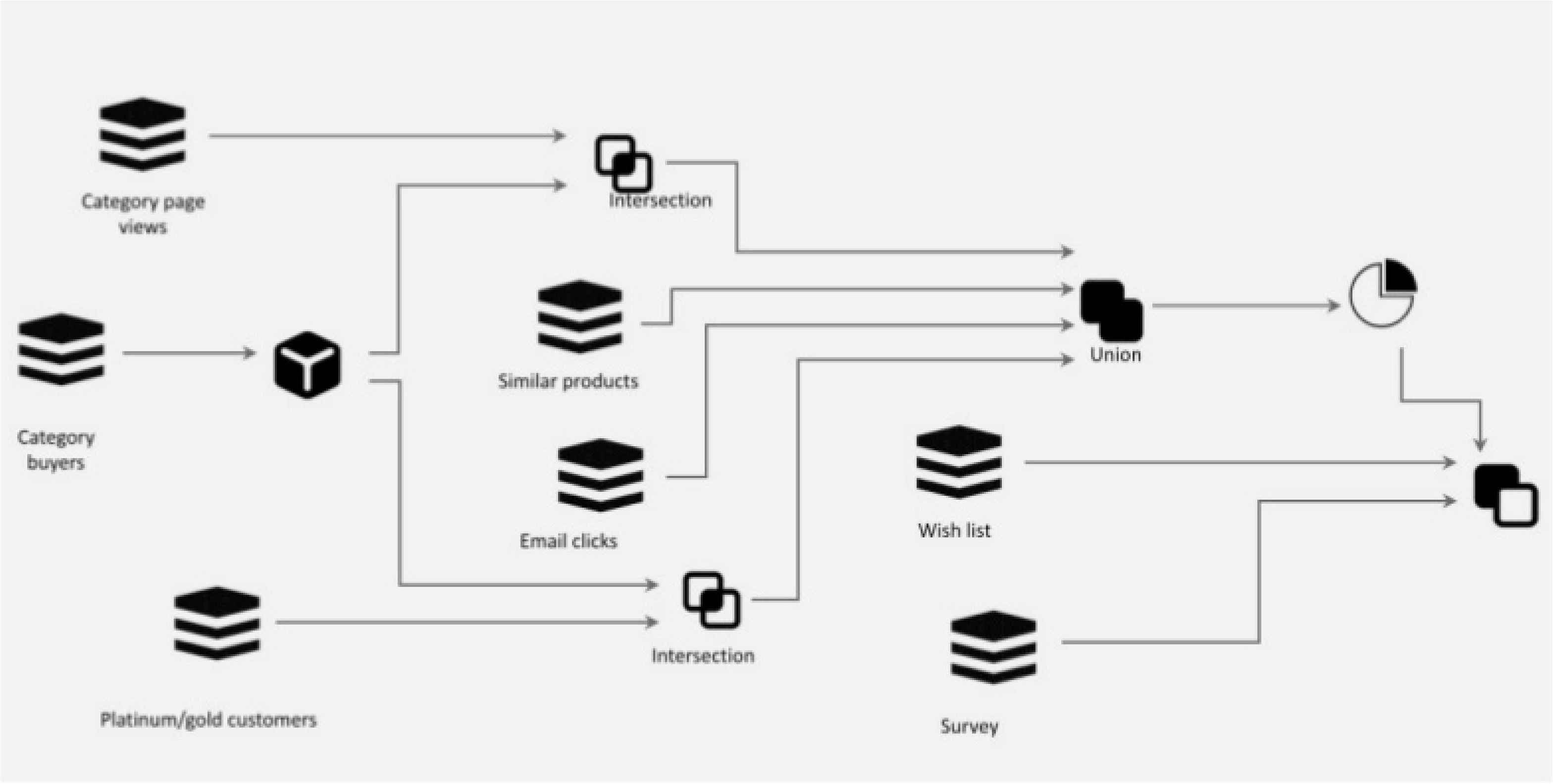
Instead of…

INTUITION

RFM

DEMOGRAPHICS

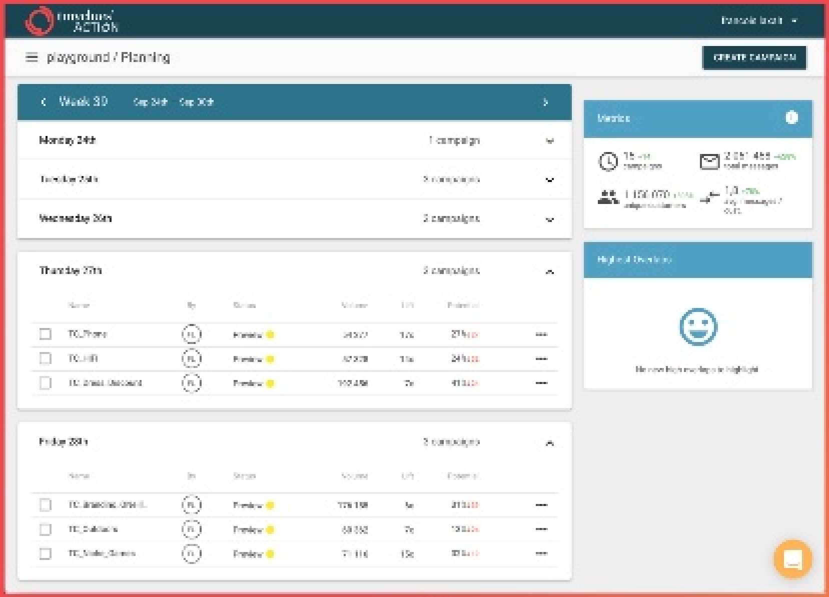
LAST PURCHASE



AI-FIRST: INTELLIGENT CAMPAIGNS IN JUST A FEW CLICKS

SPOT ON

TARGET THE FUTURE BUYERS FOR ANY PRODUCT, IN THE DAYS FOLLOWING A CAMPAIGN



☰ playground / Planning

‹ Week 39 Sep 24th - Sep 30th ›

Monday 24th — 1 campaign

Tuesday 25th — 3 campaigns

Wednesday 26th — 3 campaigns

Thursday 27th — 3 campaigns

	Name	By	Status	Volume	Lift	Potential	
□	TC_Phone	FL	Preview ●	54 577	17x	27%	⋯
□	TC_HiFi	FL	Preview ●	47 278	11x	24%	⋯
□	TC_Email_Discount	FL	Preview ●	102 458	7x	41%	⋯

Friday 28th — 3 campaigns

	Name	By	Status	Volume	Lift	Potential	
□	TC_Branding_Offer...	FL	Preview ●	176 158	5x	21%	⋯
□	TC_Outdoors	FL	Preview ●	68 352	7x	12%	⋯
□	TC_Video_Games	FL	Preview ●	71 116	15x	33%	⋯

Metrics

15 +4 campaigns

2 051 455 +20% total messages

1 150 070 +15% unique customers

1.8 +3% avg messages / cust.

Highest Overlap

No more high overlaps to highlight

START FROM YOUR CAMPAIGN IDEAS AND BUSINESS GOALS

STRATEGIC

PRIORITIZE BASED ON VALUE & MARKETING FATIGUE

EASY

BUILD SEGMENTS IN MINUTES – NO GUESSWORK & NO DATA-SCIENCE NEEDED

QUANTIFIED

ANTICIPATE & MAXIMIZE CAMPAIGN PERFORMANCE

SUCCESS STORIES

$1B+

+115%

CAMPAIGN REVENUE

Oui.sncf

TRAVEL

10M+ customers

$1B+

+30%

CAMPAIGN REVENUE

fnac

RETAIL

10M+ customers

$1B+

+151%

REVENUE PER EMAIL

LACOSTE

RETAIL / FASHION

$1B+

+178%

CAMPAIGN REVENUE

ACCOR HOTELS
Feel Welcome

HOSPITALITY

5M+ customers

$1B+

+30%

CAMPAIGN REVENUE

Club Med

HOSPITALITY

+20%

CAMPAIGN REVENUE
ONLINE & IN-STORE

CYRILLUS
PARIS

RETAIL / FASHION

$1B+

+80%

CAMPAIGN REVENUE

E-COMMERCE

10M+ customers

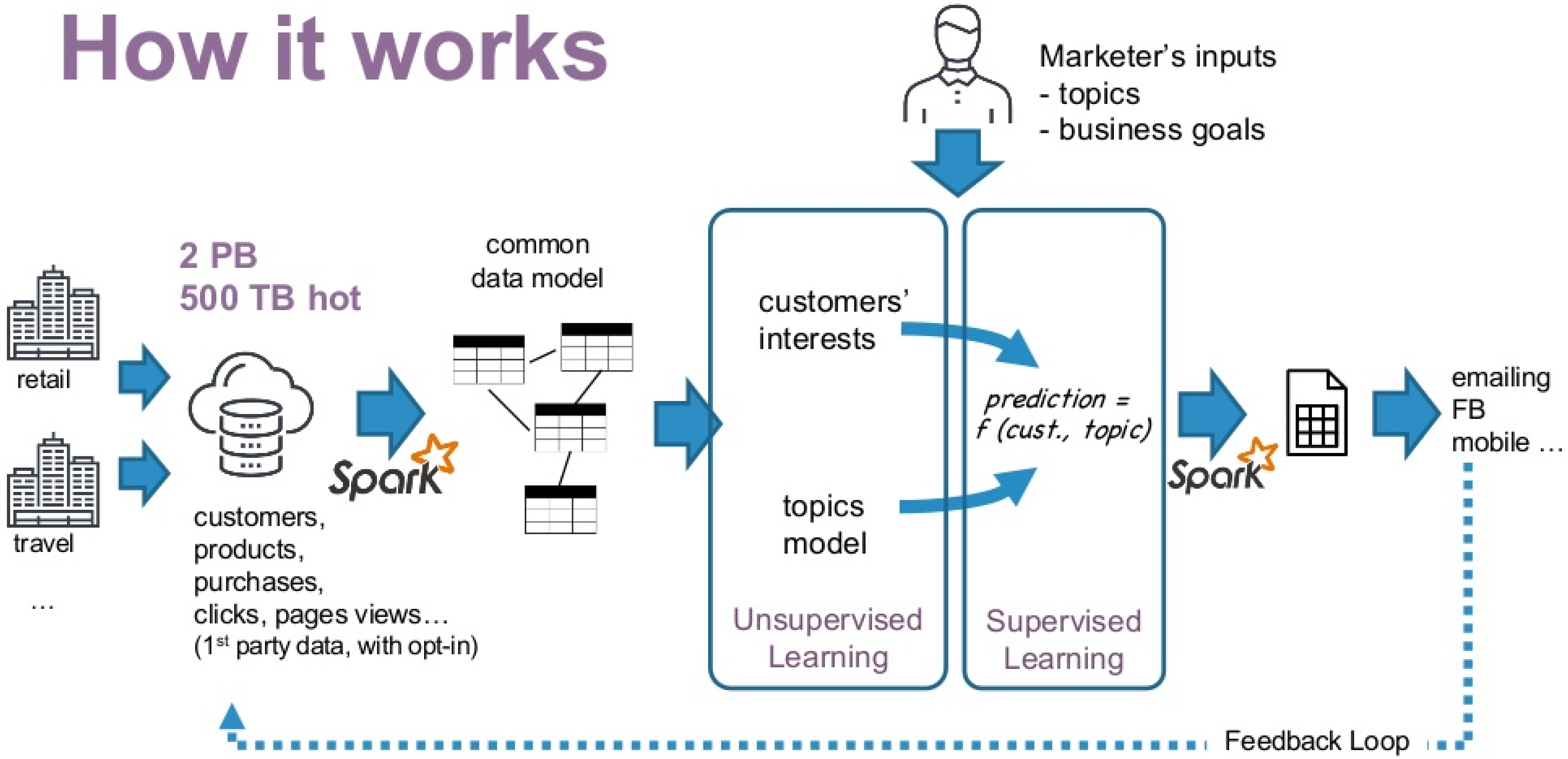
+60%

REVENUE PER EMAIL

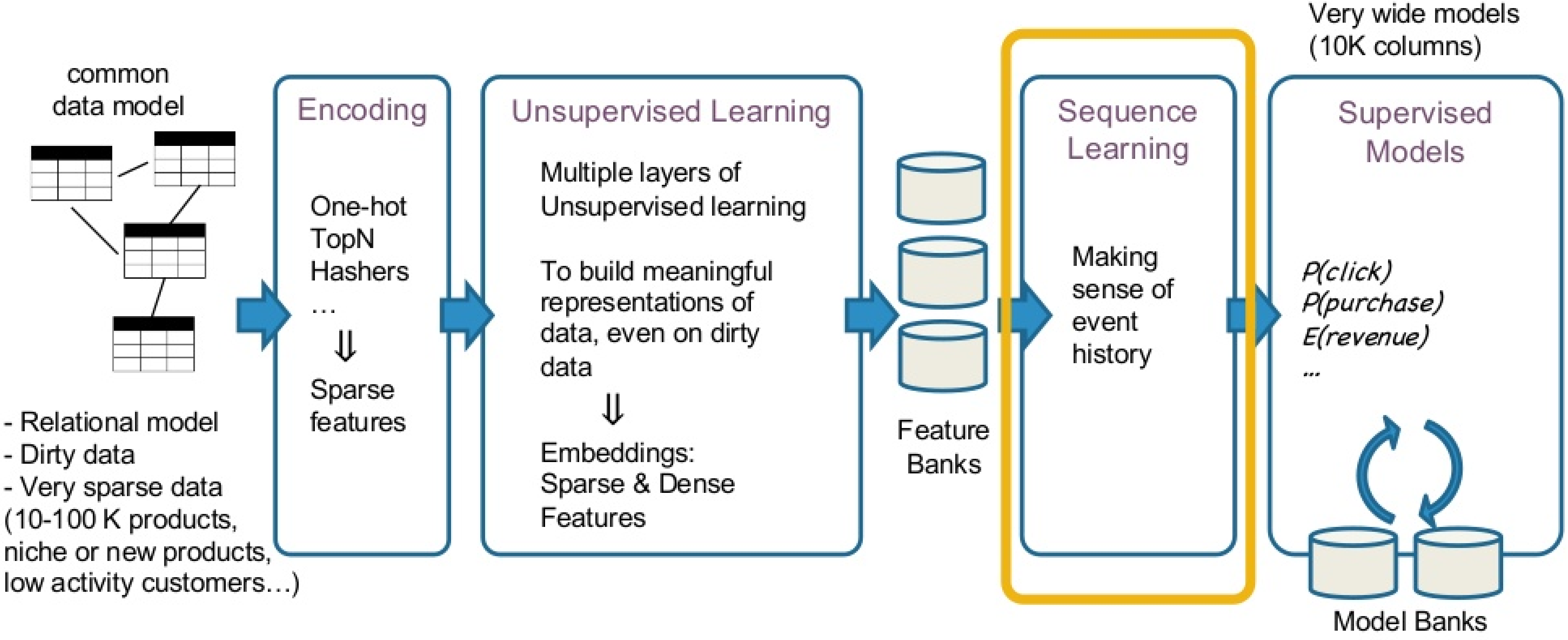
VESTIAIRE
[COLLECTIVE]

RETAIL / FASHION

How it works


Marketer’s inputs
- topics
- business goals
retail
travel
…
2 PB
500 TB hot
customers,
products,
purchases,
clicks, pages views…
(1st party data, with opt-in)
Spark
common
data model
customers’
interests
topics
model
Unsupervised
Learning
prediction =
f (cust., topic)
Supervised
Learning
Spark
emailing
FB
mobile …
Feedback Loop

Predictive architecture



common data model

- Relational model
- Dirty data
- Very sparse data (10-100 K products, niche or new products, low activity customers…)

Encoding

One-hot
TopN
Hashers
…
⇓
Sparse features

Unsupervised Learning

Multiple layers of Unsupervised learning

To build meaningful representations of data, even on dirty data

⇓

Embeddings:
Sparse & Dense Features

Feature Banks

Sequence Learning

Making sense of event history

Very wide models (10K columns)

Supervised Models

P(click)
P(purchase)
E(revenue)
…

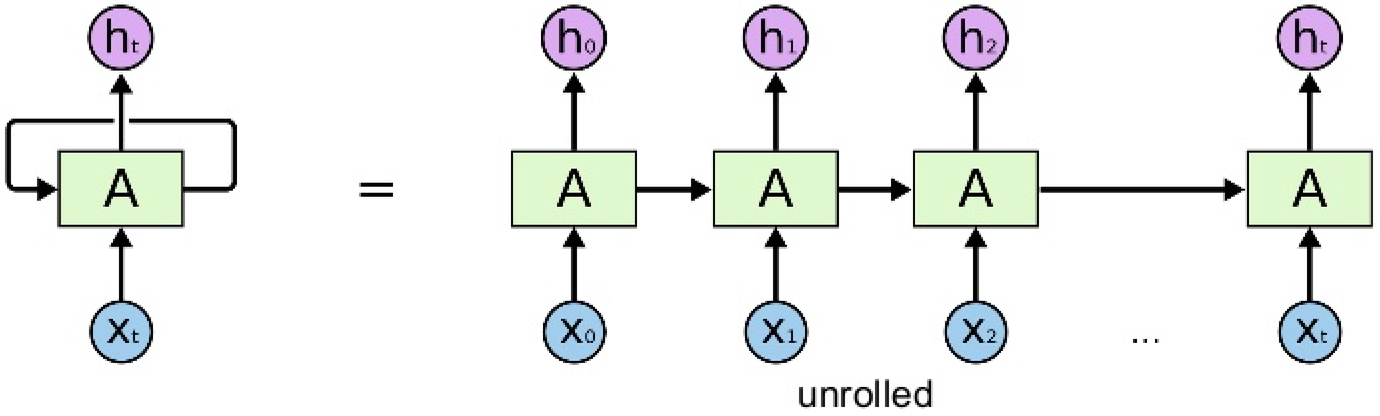
Model Banks

Working with events

- Events (page views, clicks…) are not always meaningful individually, but sequences are
- Events are ordered, and are not independent from each other
- Sequences are not all of the same length
- Can we find a model architecture leveraging on these characteristics ?

RNN: Recurrent Neural Networks

- Networks with loops in them, allowing information to persist.



- They also allow input sequences of variable length
  - you just need to pad data with zeroes $X_0..X_k$

Illustrations by Christopher Olah - Check out his blog! colah.github.io

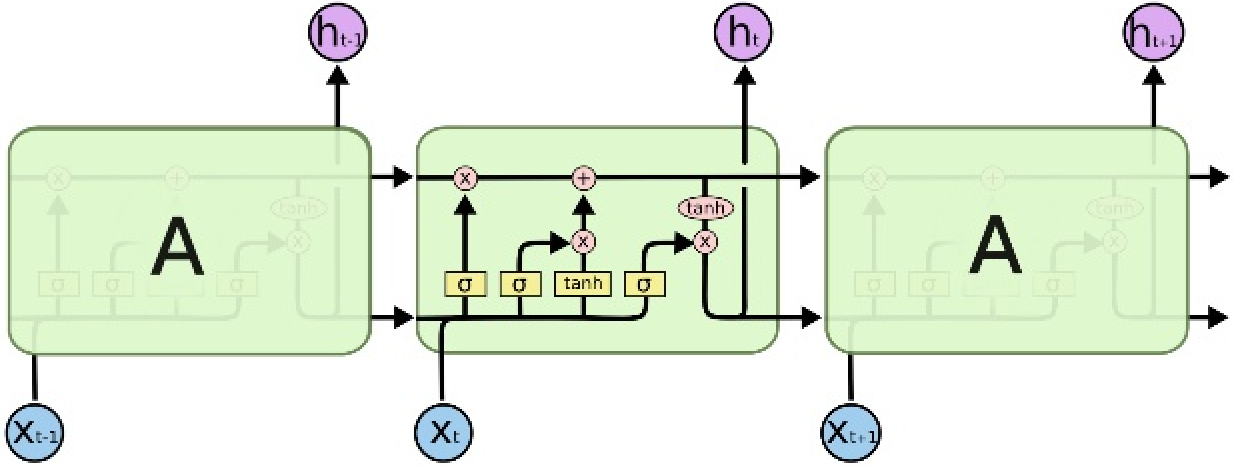
LSTM: Long Short-Term Memory

- Classical RNN can’t learn long-term dependencies with gradient descent because of vanishing or exploding gradients: they tend to forget in the long-term

- LSTMs are explicitly designed to avoid this problem
  - Invented by Hochreiter & Schmidhuber (1997)
  - Many variants exist

- LSTM have great results in speech recognition, translation, and are building block of assistants.

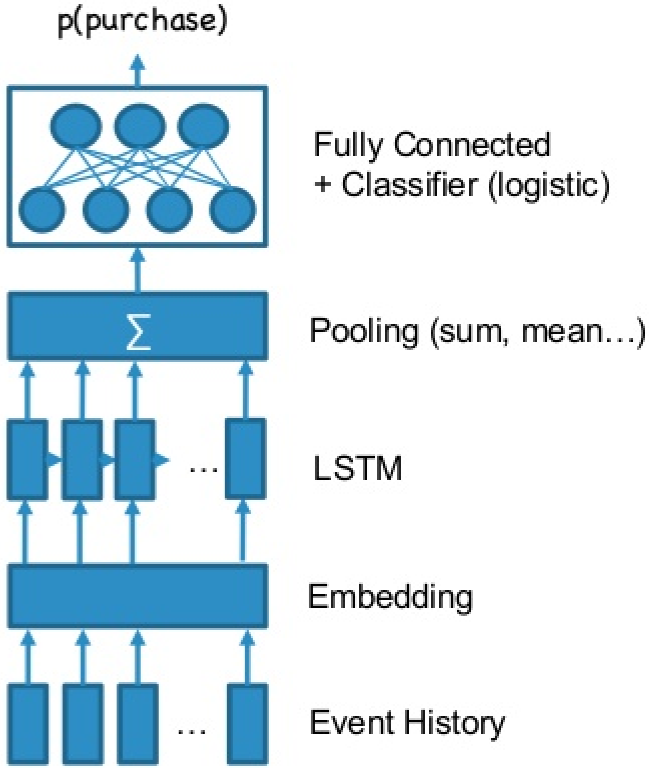
LSTM



- Cell-state is transmitted from cell to cell (top line) without going through a non-linear activation function
- The rest of the cell controls:
  - how the input and previous outputs modifies the cell state,
  - how the state and input are combined together to form output

Example of LSTM for purchase prediction

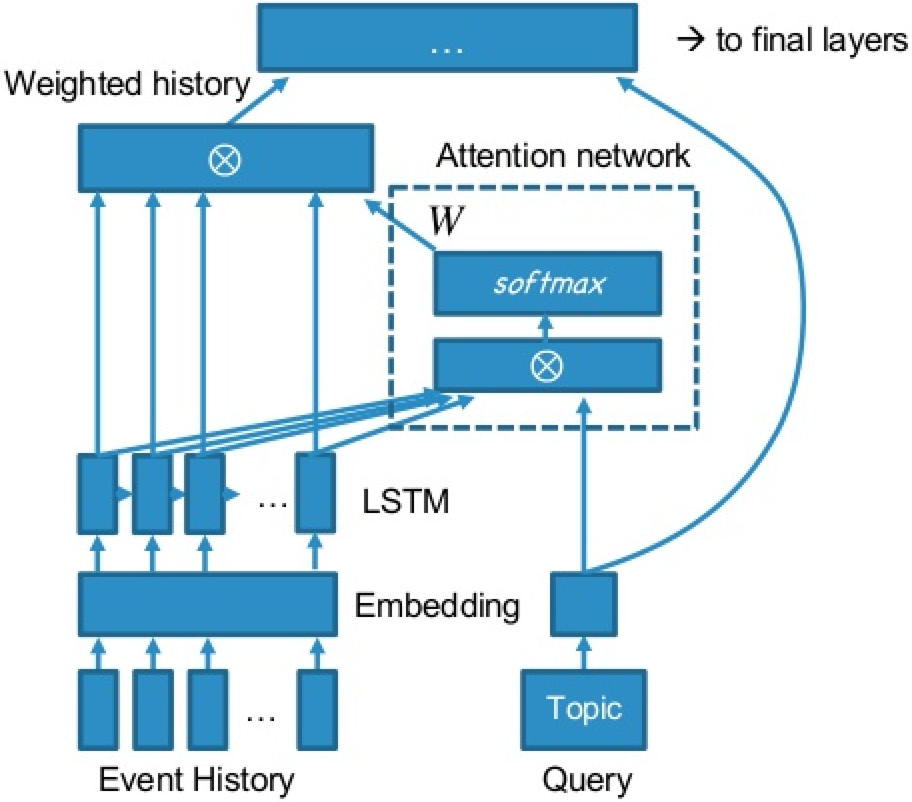
- Inputs are events (page views, clicks), padded to a max sequence length, and passed through an embedding layer
- LSTM output is aggregated with a pooling layer, and some densely connected layers
- Through gradient descent, the network will learn what event sequences are more likely to lead to the target (purchase)



"embedding": representing an information by a vector in a space, capturing its essential meaning

Bringing some focus: Attention Model

- Attention models are a way to make the network focus on elements of interest
- Introduce the notion of “Query” = what the network should focus on (topic)
- The attention network outputs weights W that modulate the importance of each LSTM output, given the topic
- This weighted and interpreted history is then used in subsequent layers for classification



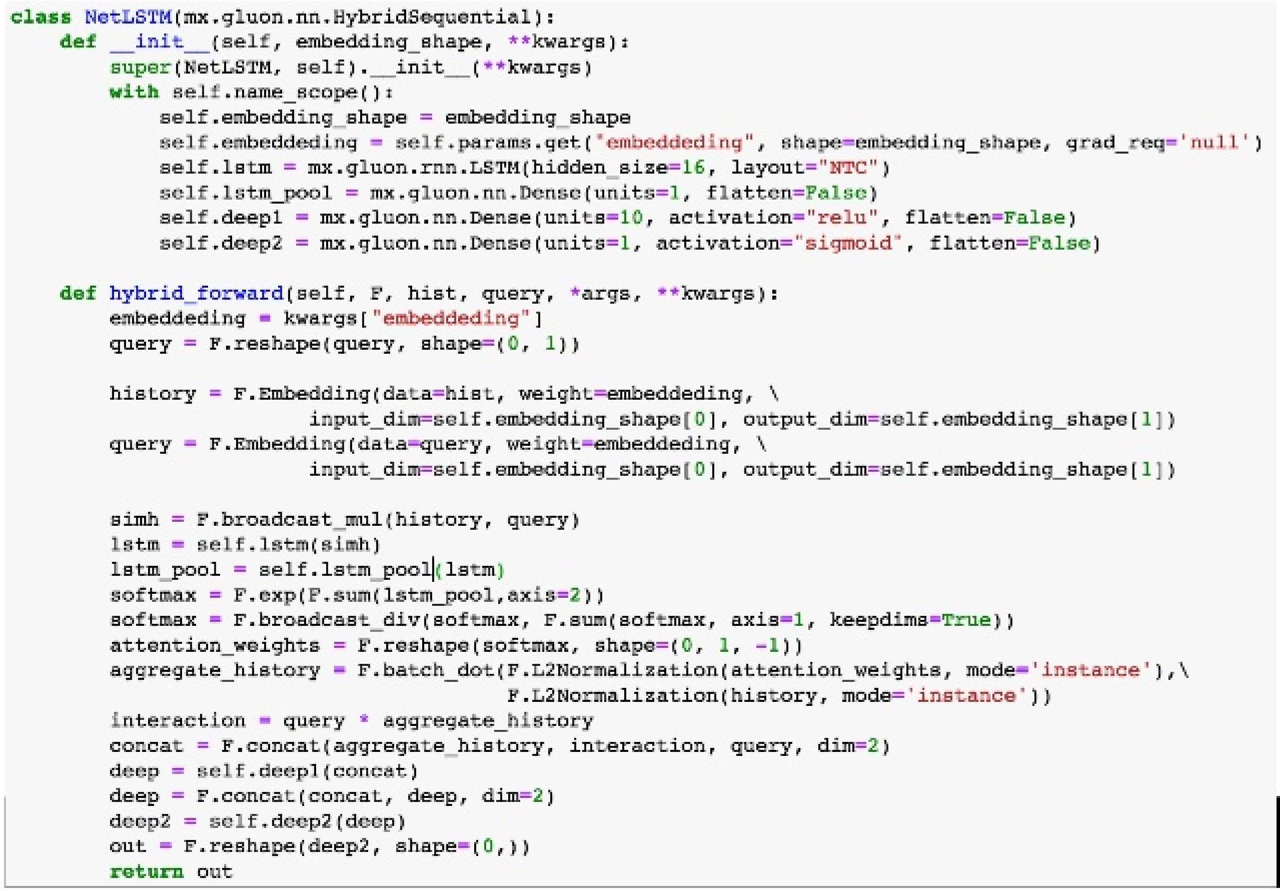
Implementation & Execution Engine

- Desired technology for production:
  - Easily distributable with Spark
  - Callable from Scala
  - Interoperability with Python (used in our Lab)
  - High performance out-of-the-box
    - should benefit from native libs
    - ability to use GPU for training phases
  - Good support of Sparse tensors

Apache MxNET

- Deep Learning framework, incubated at Apache
- Back-end in C++
- Multiple front-end languages: scala, python, Julia, R, …
- Integration with linalg native libs, including Intel MKL
- Benchmarks with GPUs are very good
- Aims at interoperability with others frameworks (ONNX, MxNET as Keras backend, etc.)

LSTM w/ Attention in Python



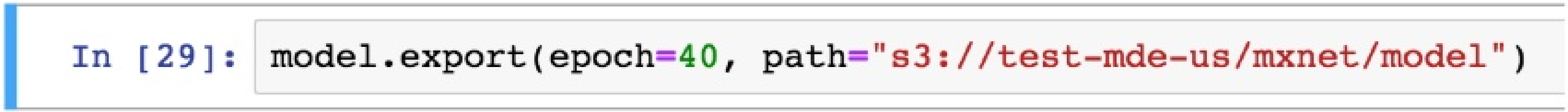
```
class NetLSTM(mx.gluon.nn.HybridSequential):
    def __init__(self, embedding_shape, **kwargs):
        super(NetLSTM, self).__init__(**kwargs)
        with self.name_scope():
            self.embedding_shape = embedding_shape
            self.embeddeding = self.params.get("embeddeding", shape=embedding_shape, grad_req='null')
            self.lstm = mx.gluon.rnn.LSTM(hidden_size=16, layout="NTC")
            self.lstm_pool = mx.gluon.nn.Dense(units=1, flatten=False)
            self.deep1 = mx.gluon.nn.Dense(units=10, activation="relu", flatten=False)
            self.deep2 = mx.gluon.nn.Dense(units=1, activation="sigmoid", flatten=False)

    def hybrid_forward(self, F, hist, query, *args, **kwargs):
        embeddeding = kwargs["embeddeding"]
        query = F.reshape(query, shape=(0, 1))

        history = F.Embedding(data=hist, weight=embeddeding, \
                        input_dim=self.embedding_shape[0], output_dim=self.embedding_shape[1])
        query = F.Embedding(data=query, weight=embeddeding, \
                        input_dim=self.embedding_shape[0], output_dim=self.embedding_shape[1])

        simh = F.broadcast_mul(history, query)
        lstm = self.lstm(simh)
        lstm_pool = self.lstm_pool(lstm)
        softmax = F.exp(F.sum(lstm_pool,axis=2))
        softmax = F.broadcast_div(softmax, F.sum(softmax, axis=1, keepdims=True))
        attention_weights = F.reshape(softmax, shape=(0, 1, -1))
        aggregate_history = F.batch_dot(F.L2Normalization(attention_weights, mode='instance'),\
                                        F.L2Normalization(history, mode='instance'))
        interaction = query * aggregate_history
        concat = F.concat(aggregate_history, interaction, query, dim=2)
        deep = self.deep1(concat)
        deep = F.concat(concat, deep, dim=2)
        deep2 = self.deep2(deep)
        out = F.reshape(deep2, shape=(0,))
        return out
```

- Written using (the very young) Gluon API

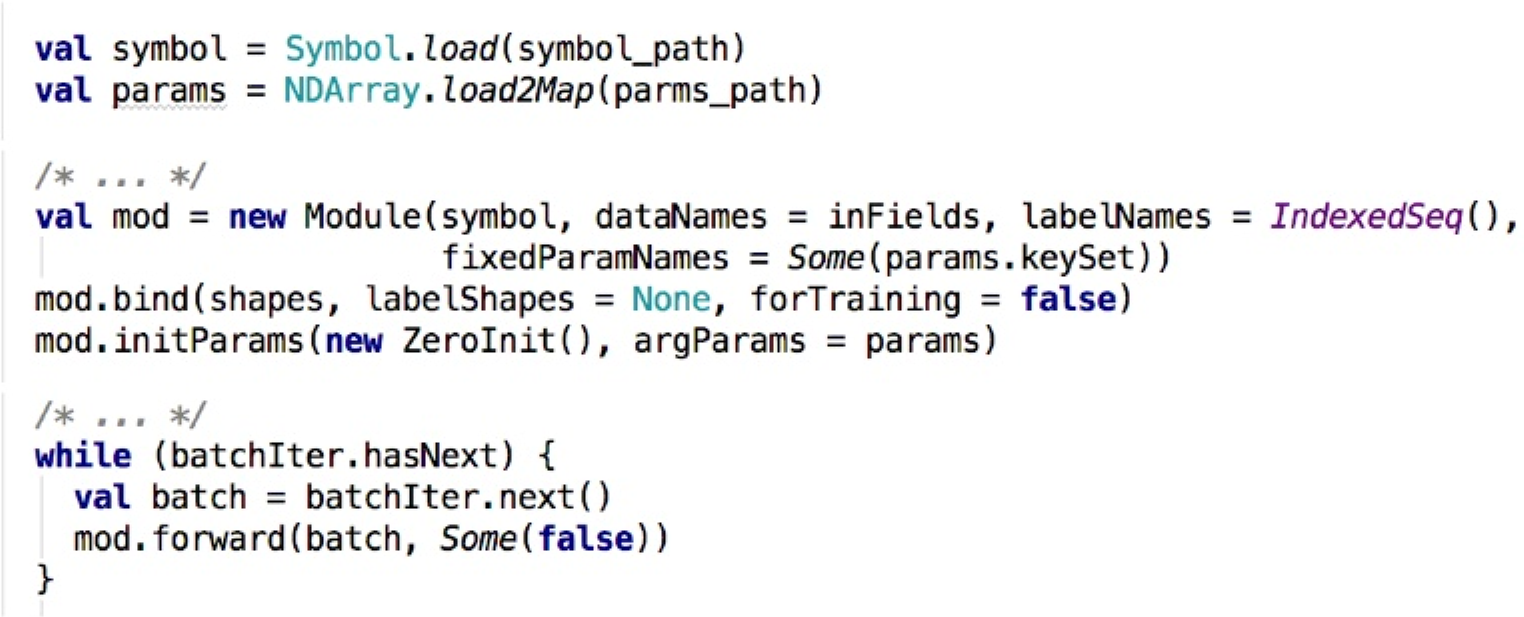
- Similar to Keras

- Can be compiled into a “Symbol” model (symbolic graph of execution)

Using in Scala a model trained in Python

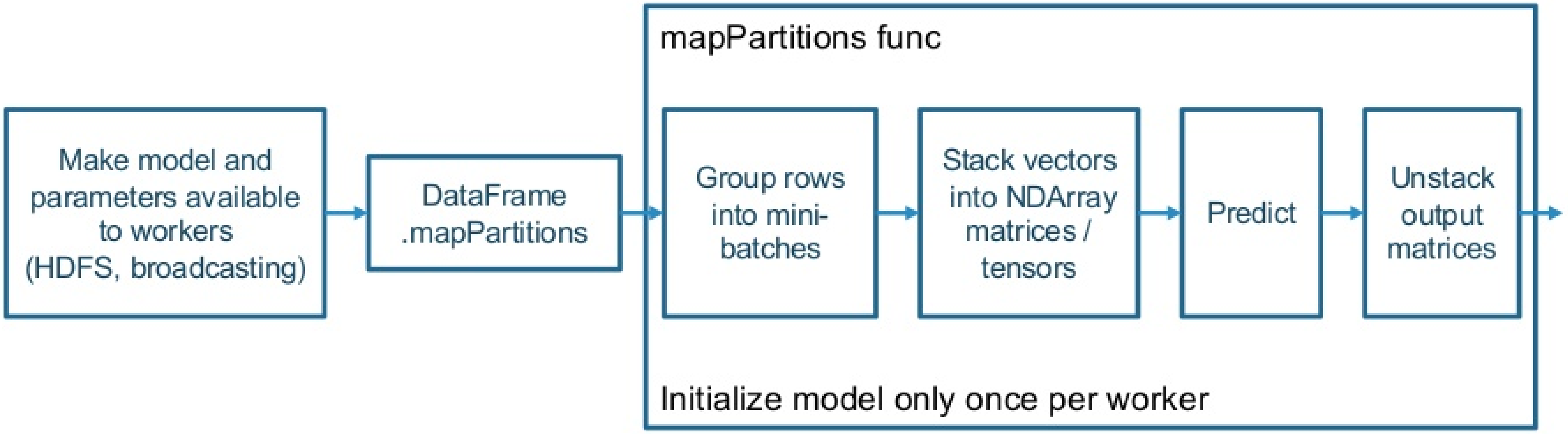


```
In [29]: model.export(epoch=40, path="s3://test-mde-us/mxnet/model")
```



```
val symbol = Symbol.load(symbol_path)
val params = NDArray.load2Map(parms_path)

/* ... */
val mod = new Module(symbol, dataNames = inFields, labelNames = IndexedSeq(),
                     fixedParamNames = Some(params.keySet))
mod.bind(shapes, labelShapes = None, forTraining = false)
mod.initParams(new ZeroInit(), argParams = params)

/* ... */
while (batchIter.hasNext) {
  val batch = batchIter.next()
  mod.forward(batch, Some(false))
}
```

Inference from a Spark pipeline


mapPartitions func
Make model and parameters available to workers (HDFS, broadcasting)
DataFrame .mapPartitions
Group rows into mini-batches
Stack vectors into NDArray matrices / tensors
Predict
Unstack output matrices
Initialize model only once per worker

- Pay attention to resource usage on workers
  - Ensure backend processing will have available CPU cores and plenty of RAM
- Pay attention to data copy operation that will happen between Spark Vectors (from java memory) and MxNET native backend

Learnings about MxNET in Scala

- MxNET is very young
  - Mixed API styles
  - Scala API is lagging Python's
    - No sparse tensors yet
  - Unhelpful error messages, especially when they come from the C++ backend
  - In Lab context (notebook, fast iteration), it feels heavy
  - Some non-trivial boilerplate code to write
  - ONNX interop has limitations

- Yet, it's very promising, and fast out-of-the-box
  - Many binaries available with hw optimization
  - Usable in Scala/Spark pipelines

Take aways

- To find the “tiny clues” within your data, you need powerful learning algorithms to discover their latent meaning

- LSTM with Attention Models are especially good when it comes to sequences of events

- Using inference models from Scala/Spark code is easy and performant with MxNET, even if this framework has still a lot of limitations

Thank you !

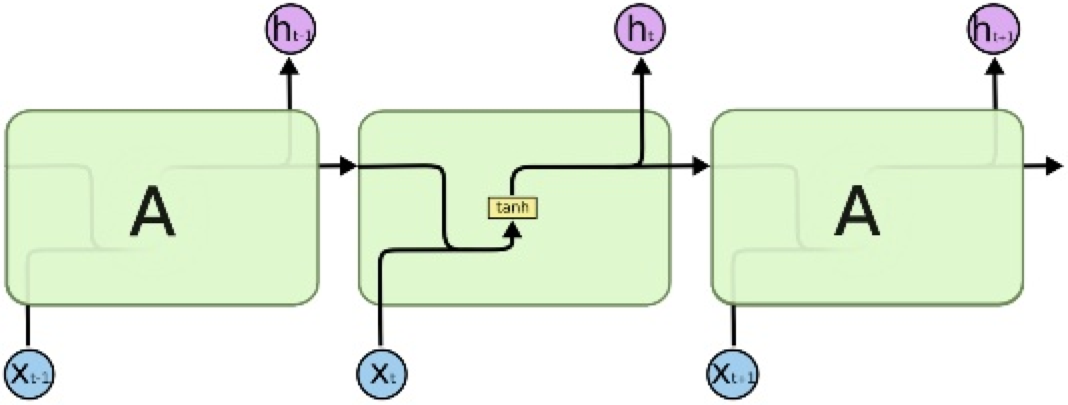
Questions ?

Reach me on twitter @mdespriee

Backup

Classical RNN have limitations

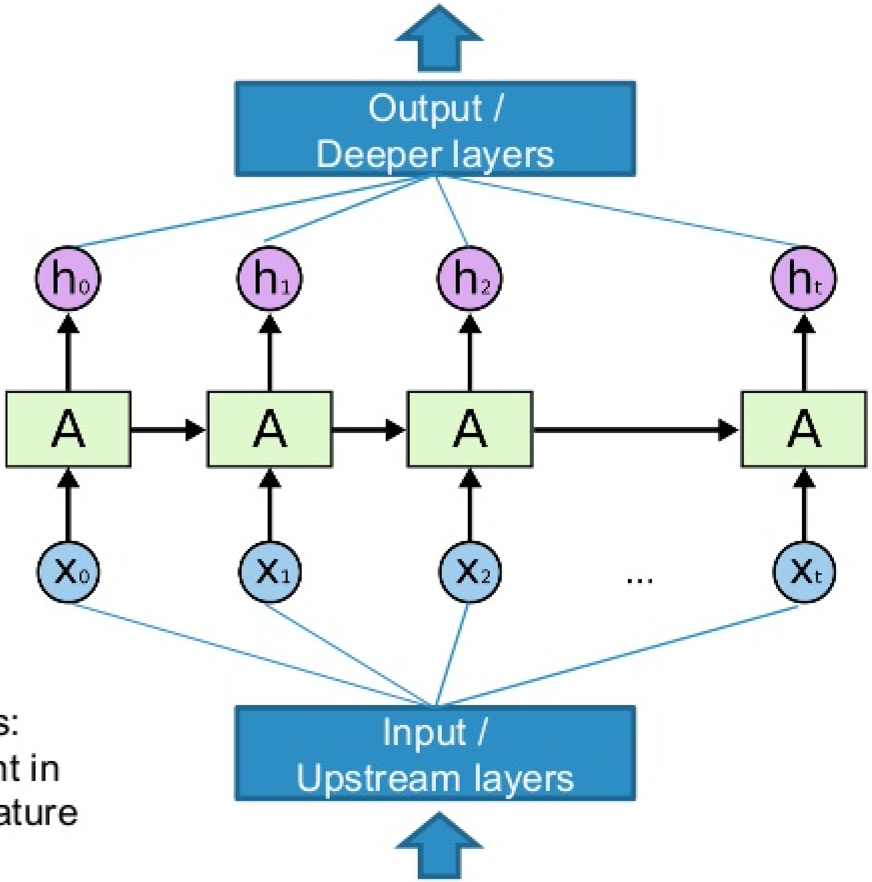
- Vanilla RNN can’t learn long-term dependencies with gradient descent because of vanishing or exploding gradients

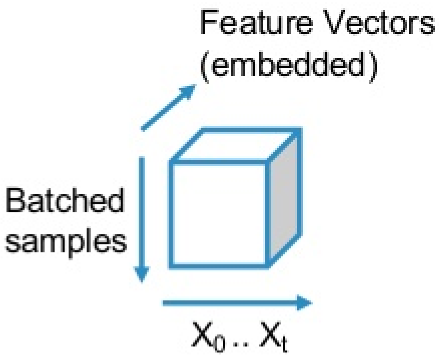


Illustrations by Christopher Olah (check out his blog!) http://colah.github.io/

RNN

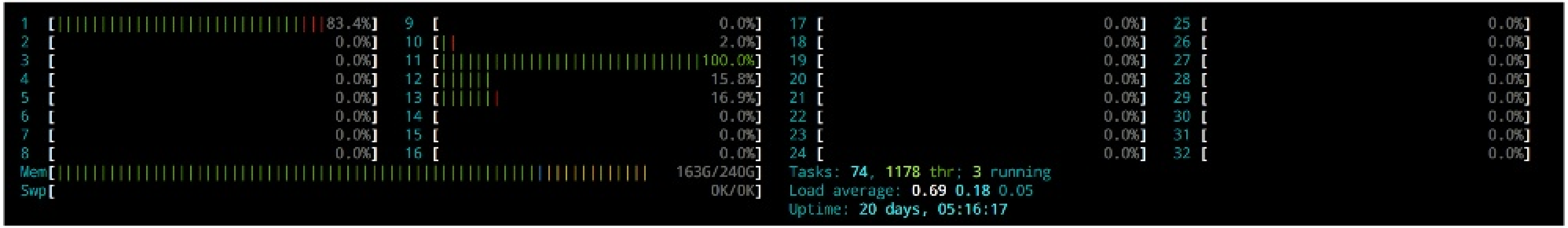
“embedding”: a compact mathematical representation of an information into a vector, capturing its semantics





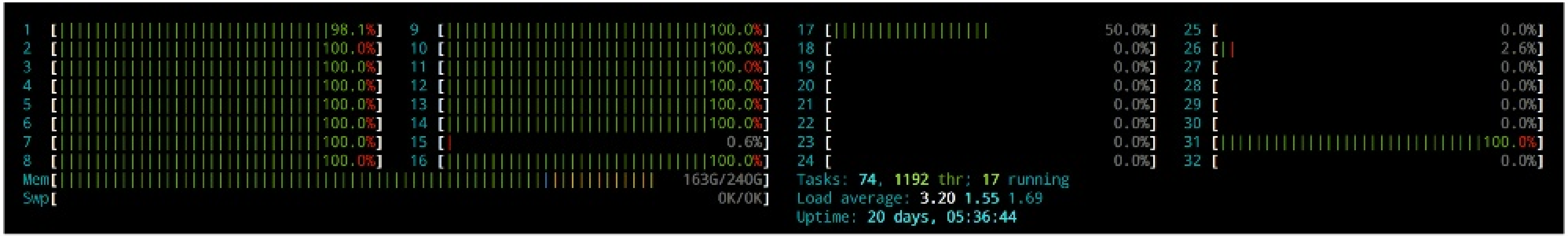
Input from upstream layers: Each X is a value at a point in time, represented by a Feature Vector

MKL impact



```
 1  [|||||||||||||||||||||||||||||83.4%]    9 [                              0.0%]   17 [                              0.0%]   25 [                              0.0%]
 2  [                              0.0%]   10 [||                            2.0%]   18 [                              0.0%]   26 [                              0.0%]
 3  [                              0.0%]   11 [||||||||||||||||||||||||||||100.0%]   19 [                              0.0%]   27 [                              0.0%]
 4  [                              0.0%]   12 [||||||                       15.8%]   20 [                              0.0%]   28 [                              0.0%]
 5  [                              0.0%]   13 [|||||||                      16.9%]   21 [                              0.0%]   29 [                              0.0%]
 6  [                              0.0%]   14 [                              0.0%]   22 [                              0.0%]   30 [                              0.0%]
 7  [                              0.0%]   15 [                              0.0%]   23 [                              0.0%]   31 [                              0.0%]
 8  [                              0.0%]   16 [                              0.0%]   24 [                              0.0%]   32 [                              0.0%]
Mem[||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||        163G/240G]   Tasks: 74, 1178 thr; 3 running
Swp[                                                                        0K/0K]   Load average: 0.69 0.18 0.05
                                                                                     Uptime: 20 days, 05:16:17
```

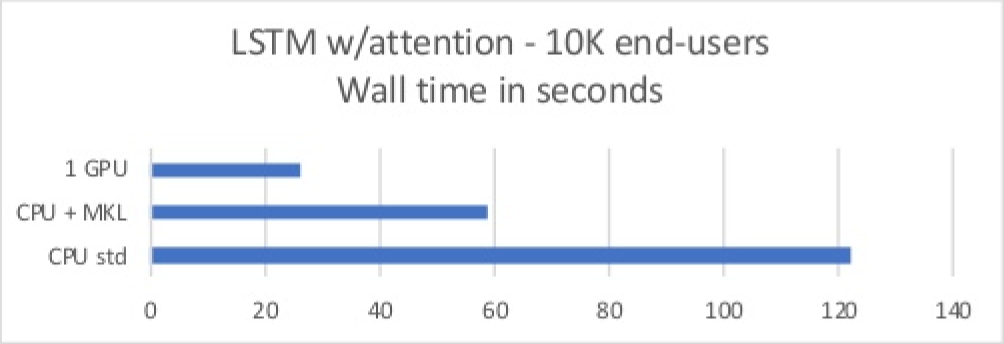
CPU times: user 4min 12s, sys: 10.4 s, total: 4min 22s Wall time: 2min 2s

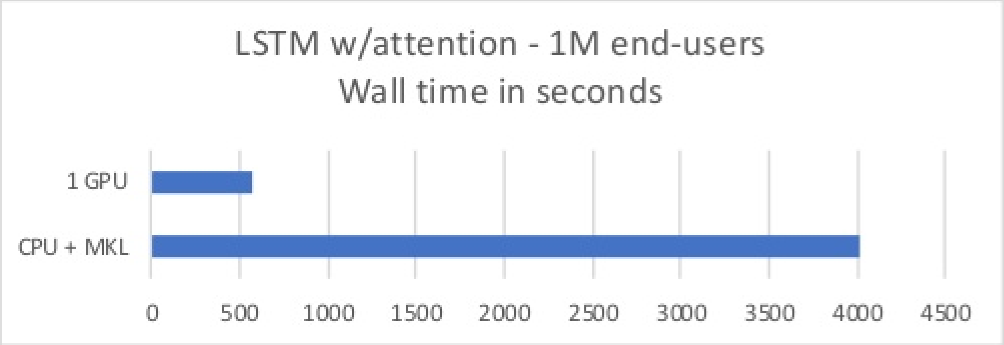


```
 1  [|||||||||||||||||||||||||||||98.1%]    9 [||||||||||||||||||||||||||||100.0%]   17 [|||||||||||||||||            50.0%]   25 [                              0.0%]
 2  [||||||||||||||||||||||||||||100.0%]   10 [||||||||||||||||||||||||||||100.0%]   18 [                              0.0%]   26 [||                            2.6%]
 3  [||||||||||||||||||||||||||||100.0%]   11 [||||||||||||||||||||||||||||100.0%]   19 [                              0.0%]   27 [                              0.0%]
 4  [||||||||||||||||||||||||||||100.0%]   12 [||||||||||||||||||||||||||||100.0%]   20 [                              0.0%]   28 [                              0.0%]
 5  [||||||||||||||||||||||||||||100.0%]   13 [||||||||||||||||||||||||||||100.0%]   21 [                              0.0%]   29 [                              0.0%]
 6  [||||||||||||||||||||||||||||100.0%]   14 [||||||||||||||||||||||||||||100.0%]   22 [                              0.0%]   30 [                              0.0%]
 7  [||||||||||||||||||||||||||||100.0%]   15 [|                             0.6%]   23 [                              0.0%]   31 [||||||||||||||||||||||||||||100.0%]
 8  [||||||||||||||||||||||||||||100.0%]   16 [||||||||||||||||||||||||||||100.0%]   24 [                              0.0%]   32 [                              0.0%]
Mem[||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||        163G/240G]   Tasks: 74, 1192 thr; 17 running
Swp[                                                                        0K/0K]   Load average: 3.20 1.55 1.69
                                                                                     Uptime: 20 days, 05:36:44
```

CPU times: user 15min 41s, sys: 40.6 s, total: 16min 21s Wall time: 59.6 s

Performance of training





<u>Disclaimer</u>: These measurements are indicative, and vary a lot depending on many parameters.