SCIENCE
PASSION
TECHNOLOGY

Architecture of ML Systems*
04 Model Deployment and Serving

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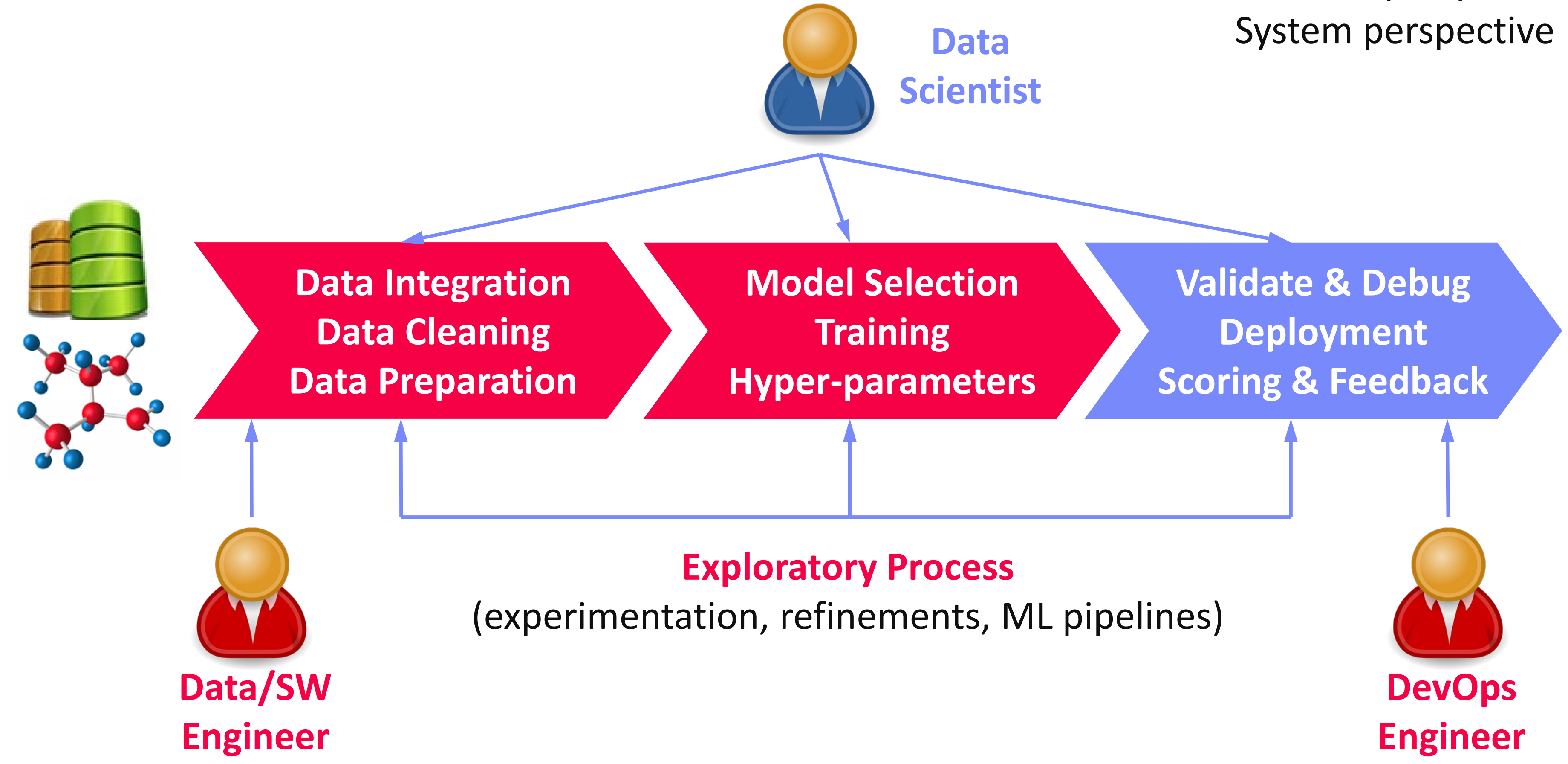
ISDS

Recap: The Data Science Lifecycle

Data-centric View:
Application perspective
Workload perspective
System perspective



Exploratory Process
(experimentation, refinements, ML pipelines)

Agenda

- **Model Exchange and Serving**
- **Model Monitoring and Updates**

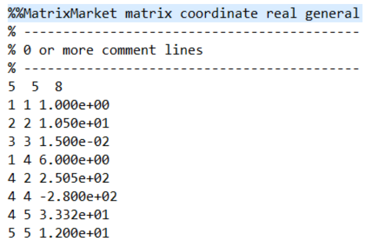
Model Exchange and Serving

Model Exchange Formats

- **Definition Deployed Model**
  - **#1 Trained ML model** (weight/parameter matrix)
  - **#2 Trained weights AND operator graph** / entire ML pipeline

    → especially for DNN (many weight/bias tensors, hyper parameters, etc)

- **Recap: Data Exchange Formats** (model + meta data)
  - General-purpose formats: **CSV**, **JSON**, **XML**, **Protobuf**
  - Sparse matrix formats: **matrix market**, **libsvm**
  - Scientific formats: **NetCDF**, **HDF5**
  - ML-system-specific binary formats (e.g., SystemDS, PyTorch serialized)



```
%%MatrixMarket matrix coordinate real general
% ------------------------------------------
% 0 or more comment lines
% ------------------------------------------
5  5  8
1 1 1.000e+00
2 2 1.050e+01
3 3 1.500e-02
1 4 6.000e+00
4 2 2.505e+02
4 4 -2.800e+02
4 5 3.332e+01
5 5 1.200e+01
```

- **Problem ML System Landscape**
  - Different languages and frameworks, including versions
  - Lack of standardization → **DSLs for ML is wild west**

Model Exchange Formats, cont.

- **Why Open Standards?**
  - Open source allows inspection but no control
  - Open governance necessary for open standard
  - Cons: needs adoption, moves slowly

Open Standards for
Machine Learning
Deployment

Nick Pentreath
Principal Engineer

@MLnick

IBM **Developer**

[Nick Pentreath: Open Standards for Machine Learning Deployment, **bbuzz 2019**]

- **#1 Predictive Model Markup Language (PMML)**
  - Model exchange format in XML, created by Data Mining Group 1997
  - Package model weights, hyper parameters, and **limited set of algorithms**
- **#2 Portable Format for Analytics (PFA)**
  - Attempt to fix limitations of PMML, created by Data Mining Group
  - JSON and AVRO exchange format
  - **Minimal functional math language** → arbitrary custom models
  - Scoring in JVM, Python, R

Model Exchange Formats, cont.

- **#3 Open Neural Network Exchange (ONNX)**
  - **Model exchange format** (data and operator graph) via Protobuf
  - First Facebook and Microsoft, then IBM, Amazon → PyTorch, MXNet
  - Focused on **deep learning and tensor operations**
  - ONNX-ML: support for traditional ML algorithms
  - Scoring engine: https://github.com/Microsoft/onnxruntime
  - Cons: **low level** (e.g., fused ops), **DNN-centric** → ONNX-ML

- **TensorFlow Saved Models**
  - **TensorFlow-specific exchange format** for model and operator graph
  - Freezes input weights and literals, for additional optimizations (e.g., constant folding, quantization, etc)
  - Cloud providers may not be interested in open exchange standards

ML Systems for Serving

- **#1 Embedded ML Serving**
  - TensorFlow Lite and new language bindings (small footprint, dedicated HW acceleration, APIs, and models: MobileNet, SqueezeNet)
  - SystemML JMLC (Java ML Connector)

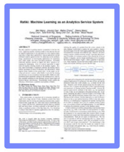
- **#2 ML Serving Services**
  - Motivation: Complex DNN models, ran on dedicated HW
  - RPC/REST interface for applications
  - TensorFlow Serving: configurable serving w/ batching
  - Clipper: Decoupled multi-framework scoring, w/ batching and result caching
  - Pretzel: Batching and multi-model optimizations in ML.NET
  - Rafiki: Optimization for accuracy under latency constraints, and batching and multi-model optimizations

Example:
Google Translate
140B words/day
→ **82K GPUs** in 2016

[Christopher Olston et al: TensorFlow-Serving: Flexible, High-Performance ML Serving. NIPS **ML Systems 2017**]

[Daniel Crankshaw et al: Clipper: A Low-Latency Online Prediction Serving System. **NSDI 2017**]

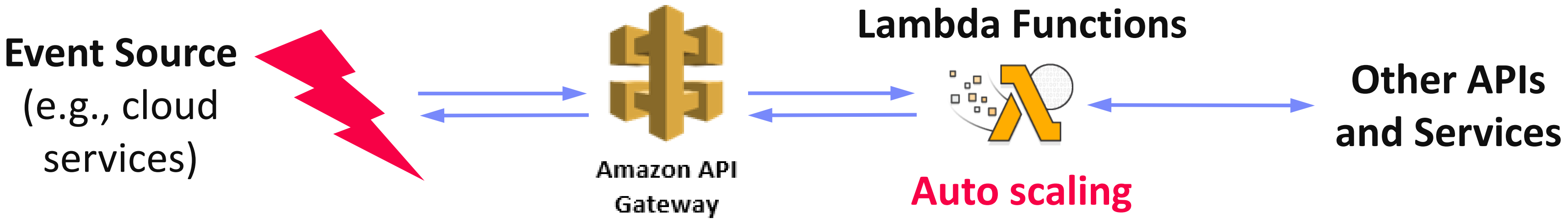
[Yunseong Lee et al.: PRETZEL: Opening the Black Box of Machine Learning Prediction Serving Systems. **OSDI 2018**]


[Wei Wang et al: Rafiki: Machine Learning as an Analytics Service System. **PVLDB 2018**]

Serverless Computing

[Joseph M. Hellerstein et al: Serverless Computing: One Step Forward, Two Steps Back. **CIDR 2019**]

- **Definition Serverless**
  - **FaaS:** functions-as-a-service (event-driven, stateless input-output mapping)
  - Infrastructure for deployment and auto-scaling of APIs/functions
  - Examples: **Amazon Lambda**, **Microsoft Azure Functions**, etc



Auto scaling
Pay-per-request
(1M x 100ms = 0.2$)

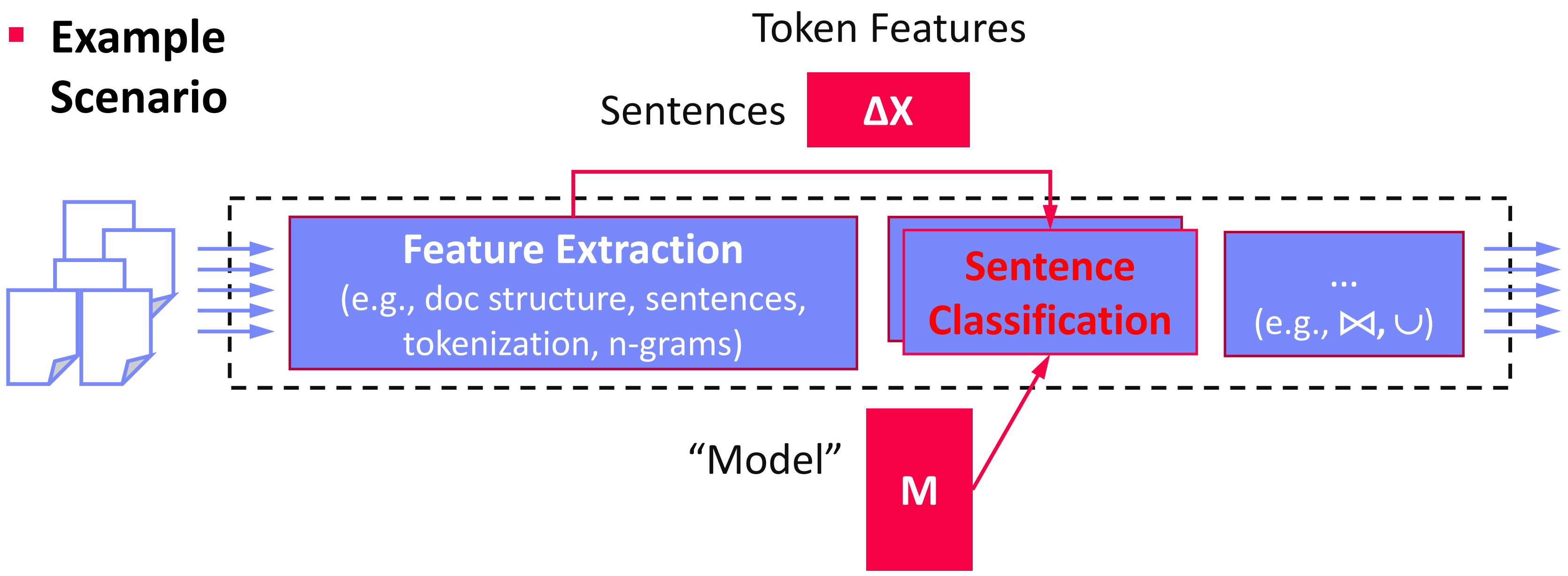
- **Example**

```
import com.amazonaws.services.lambda.runtime.Context;
import com.amazonaws.services.lambda.runtime.RequestHandler;

public class MyHandler implements RequestHandler<Tuple, MyResponse> {
    @Override
    public MyResponse handleRequest(Tuple input, Context context) {
       return expensiveModelScoring(input); // with read-only model
    }
}
```

Example SystemDS JMLC

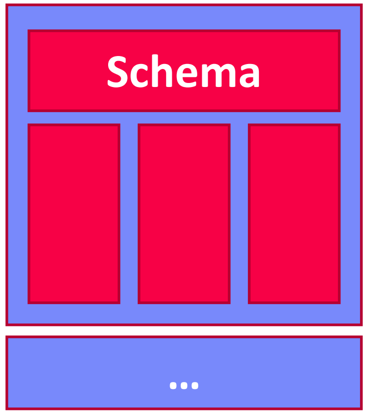
- **Example Scenario**



- **Challenges**
  - Scoring part of larger **end-to-end pipeline** → **Embedded scoring**
  - External parallelization w/o materialization
  - Simple **synchronous scoring** → **Latency ⇒ Throughput**
  - **Data size** (tiny ΔX, huge model M) → **Minimize overhead per ΔX**
  - **Seamless integration** & model consistency → **Token inputs & outputs**

Example SystemDS JMLC, cont.

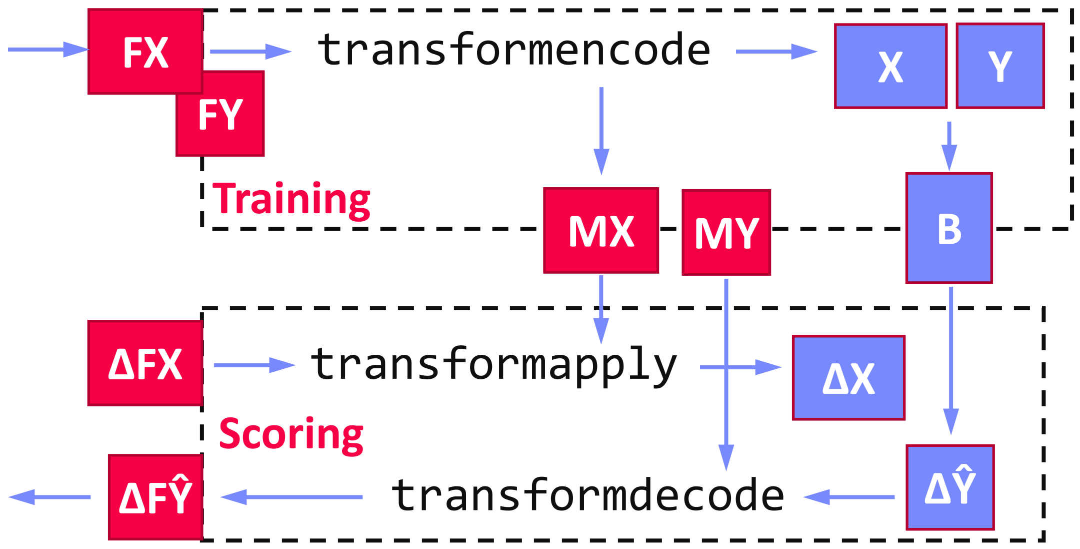
- **Background: Frame**
  - **Abstract data type with schema** (boolean, int, double, string)
  - Column-wise block layout
  - Local/distributed operations: e.g., indexing, append, **transform**



Distributed representation:
? x ncol(F) blocks

(shuffle-free conversion of csv / datasets)

- **Data Preparation via Transform**



Example SystemML JMLC, cont.

- **Motivation**
  - ➔ **Embedded scoring**
  - ➔ **Latency ⇒ Throughput**
  - ➔ **Minimize overhead per ΔX**
- **Example**

➔

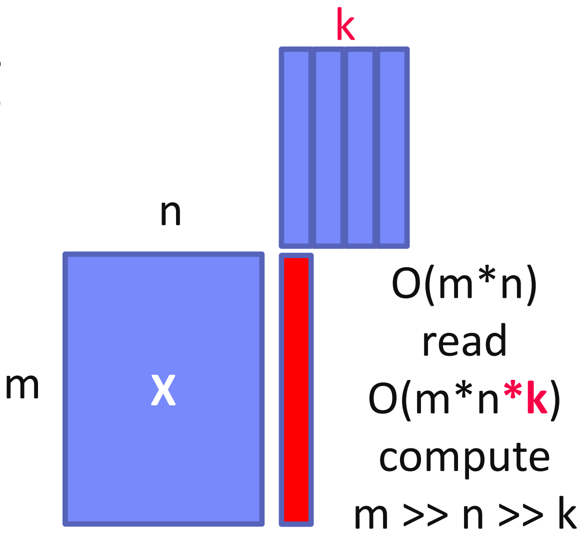
Typical compiler/runtime overheads:

Script parsing and config:	**~100ms**
Validation, compile, IPA:	**~10ms**
HOP DAG (re-)compile:	**~1ms**
Instruction execute:	**<0.1µs**

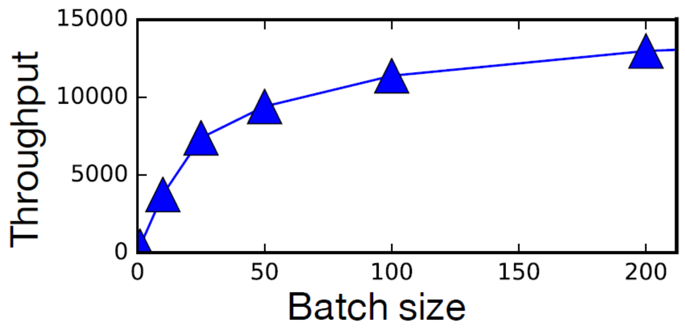
```
                                    // single-node, no evictions,
1: Connection conn = new Connection();   // no recompile, no multithread.
2: PreparedScript pscript = conn.prepareScript(
       getScriptAsString("glm-predict-extended.dml"),
       new String[]{"FX","MX","MY","B"}, new String[]{"FY"});
3: // ... Setup constant inputs
4: for( Document d : documents ) {
5:     FrameBlock FX = ...; //Input pipeline
6:     pscript.setFrame("FX", FX);
7:     FrameBlock FY = pscript.executeScript().getFrame("FY");
8:     // ... Remaining pipeline
9: }                                // execute precompiled script
                                    // many times
```

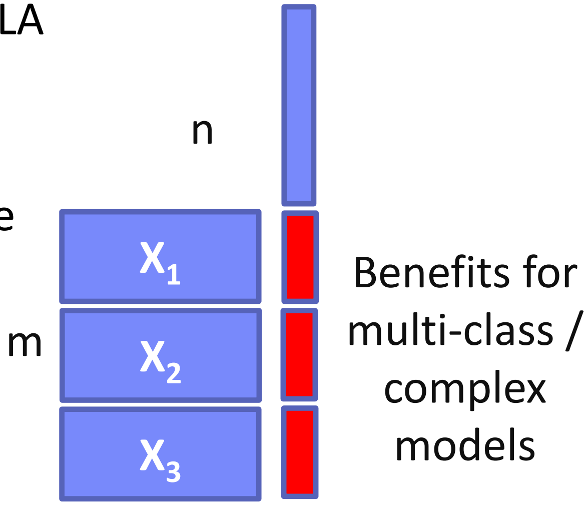
Serving Optimizations – Batching

- **Recap: Model Batching** (see **Data Access**)
  - One-pass evaluation of multiple configurations
  - EL, CV, feature selection, hyper parameter tuning
  - E.g.: **TUPAQ** [SoCC'16], **Columbus** [SIGMOD'14
- **Data Batching**
  - Batching to utilize the HW more efficiently under SLA
  - **Use case:** multiple users use the same model (wait and collect user request and merge)
  - **Adaptive:** additive increase, multiplicative decrease



[Clipper @ NSDI'17]





Serving Optimizations – Quantization

Data Access Methods

- **Quantization**
  - **Lossy compression via ultra-low precision / fixed-point**
  - Ex.: **62.7% energy** spent on data movement

[Amirali Boroumand et al.: Google Workloads for Consumer Devices: Mitigating Data Movement Bottlenecks. **ASPLOS 2018**]

- **Quantization for Model Scoring**
  - Usually **much smaller data types** (e.g., **UINT8**)
  - Quantization of model weights, and sometimes also activations
    → reduced memory requirements and better latency / throughput (SIMD)

```
import tensorflow as tf
converter = tf.lite.TFLiteConverter.from_saved_model(saved_model_dir)
converter.optimizations = [tf.lite.Optimize.OPTIMIZE_FOR_SIZE]
tflite_quant_model = converter.convert()
```

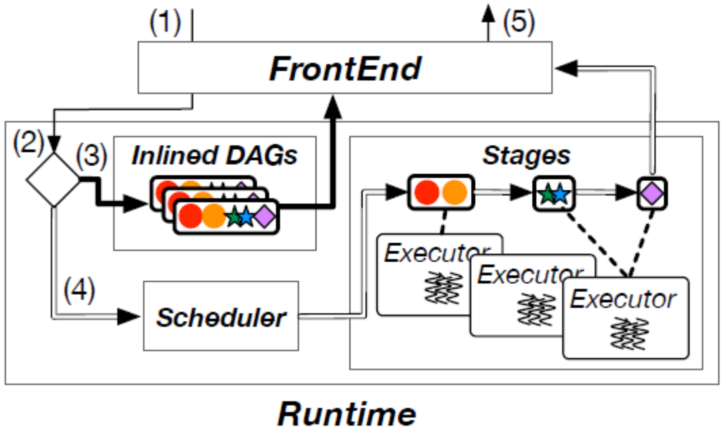
[**Credit:** https://www.tensorflow.org/lite/performance/post_training_quantization]

Serving Optimizations – MQO

- **Result Caching**
  - Establish a function cache for X → Y (memoization of deterministic function evaluation)

```
Predict(m: ModelId, x: X) -> y: Y
```

- **Multi Model Optimizations**
  - Same input fed into multiple partially redundant model evaluations
  - Common subexpression elimination between prediction programs
  - Done during compilation or runtime
  - In PRETZEL, programs compiled into physical stages and registered with the runtime + caching for stages (decided based on hashing the inputs)



[Yunseong Lee et al.: PRETZEL: Opening the Black Box of Machine Learning Prediction Serving Systems. **OSDI 2018**]

Serving Optimizations – Compilation

04 Adaptation, Fusion, and JIT

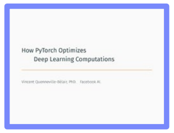
- **TensorFlow `tf.compile`**
  - Compile entire TF graph into binary function w/ low footprint
  - **Input:** Graph, config (feeds+fetches w/ fixes shape sizes)
  - **Output:** x86 binary and C++ header (e.g., inference)
  - **Specialization for frozen model and sizes**

[Chris Leary, Todd Wang: XLA – TensorFlow, Compiled!, **TF Dev Summit 2017**]

- **PyTorch Compile**
  - Compile Python functions into ScriptModule/ScriptFunction
  - Lazily collect operations, optimize, and JIT compile
  - Explicit `jit.script` call or `@torch.jit.script`

```
a = torch.rand(5)
def func(x):
  for i in range(10):
    x = x * x # unrolled into graph
  return x

jitfunc = torch.jit.script(func) # JIT
jitfunc.save("func.pt")
```

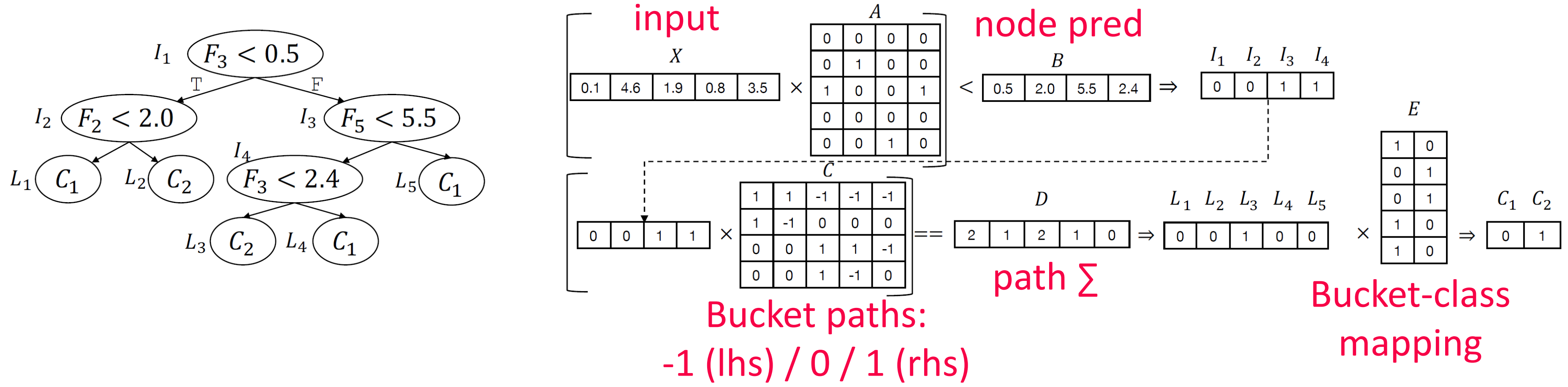

How PyTorch Optimizes
Deep Learning Computations
Vincent Quenneville-Bélair, PhD. Facebook AI.

[Vincent Quenneville-Bélair: How PyTorch Optimizes Deep Learning Computations, **Guest Lecture Stanford 2020**]

Serving Optimizations – Model Vectorization

- **HummingBird** [https://github.com/microsoft/hummingbird]
  - Compile ML scoring pipelines into tensor ops
  - Tree-based models (GEMM, 2x tree traversal)

[Supun Nakandala et al: A Tensor Compiler for Unified Machine Learning Prediction Serving. **OSDI 2020**]



$$X = \begin{bmatrix} 0.1 & 4.6 & 1.9 & 0.8 & 3.5 \end{bmatrix} \times A = \begin{bmatrix} 0&0&0&0\\0&1&0&0\\1&0&0&1\\0&0&0&0\\0&0&1&0 \end{bmatrix} < B = \begin{bmatrix} 0.5 & 2.0 & 5.5 & 2.4 \end{bmatrix} \Rightarrow \begin{array}{cccc} I_1 & I_2 & I_3 & I_4 \\ 0&0&1&1 \end{array}$$

$$\begin{bmatrix} 0&0&1&1 \end{bmatrix} \times C = \begin{bmatrix} 1&1&-1&-1&-1\\1&-1&0&0&0\\0&0&1&1&-1\\0&0&1&-1&0 \end{bmatrix} == D = \begin{bmatrix} 2&1&2&1&0 \end{bmatrix} \Rightarrow \begin{array}{ccccc} L_1 & L_2 & L_3 & L_4 & L_5 \\ 0&0&1&0&0 \end{array} \times E = \begin{bmatrix} 1&0\\0&1\\0&1\\1&0\\1&0 \end{bmatrix} \Rightarrow \begin{array}{cc} C_1 & C_2 \\ 0&1 \end{array}$$

- **Model Distillation**
  - Ensembles of models → single NN model
  - Specialized models for different classes (found via differences to generalist model)
  - Trained on soft targets (softmax w/ temperature T)

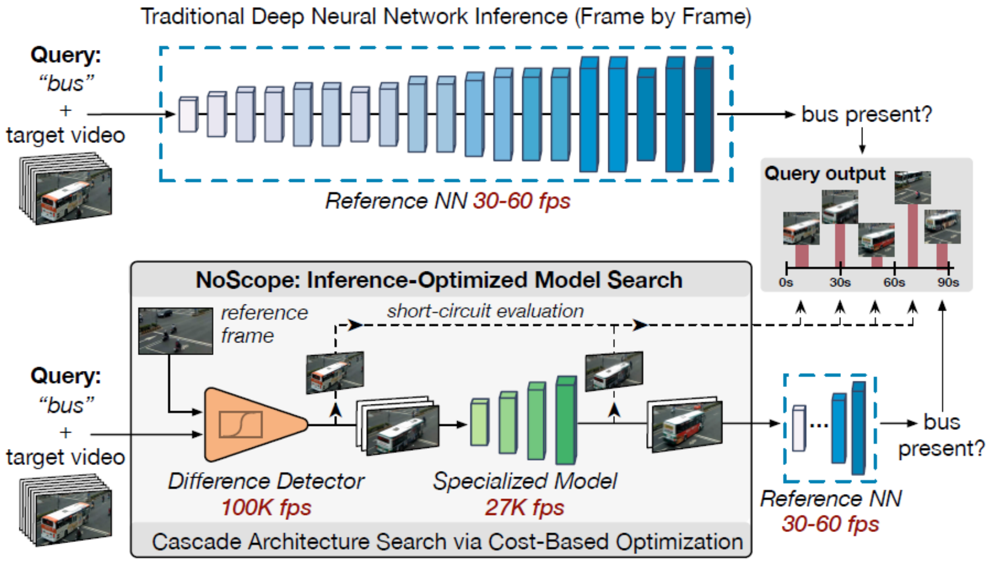
[Geoffrey E. Hinton, Oriol Vinyals, Jeffrey Dean: Distilling the Knowledge in a Neural Network. **CoRR 2015**]

$$q_i = \frac{exp(z_i/T)}{\sum_j exp(z_j/T)}$$

Serving Optimizations – Specialization

- **NoScope Architecture**
  - Baseline: YOLOv2 on 1 GPU per video camera @30fps
  - Optimizer to find filters

[Daniel Kang et al: NoScope: Optimizing Deep CNN-Based Queries over Video Streams at Scale. **PVLDB 2017**]



- **#1 Model Specialization**
  - Given query and baseline model
  - Trained shallow NN (based on AlexNet) on output of baseline model
  - Short-circuit if prediction with high confidence

- **#2 Difference Detection**
  - Compute difference to ref-image/earlier-frame
  - Short-circuit w/ ref label if no significant difference

Model Monitoring and Updates

Part of Model Management and **MLOps**
(see **Model Selection & Management**)

Model Deployment Workflow

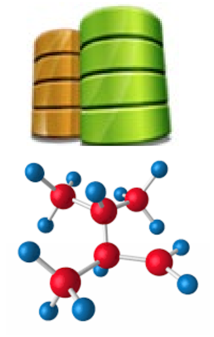
Data Integration
Data Cleaning
Data Preparation

Model Selection
Training
Hyper-parameters

#1 Model Deployment

MX **MY** **B**

Prediction Requests



#2 Continuous Data Validation / Concept Drift Detection

Model Serving

#3 Model Monitoring

#4 Periodic / Event-based Re-Training & Updates
(automatic / semi-manual)

DevOps Engineer

Monitoring Deployed Models

Google
Data Management Challenges in Production Machine Learning
Neoklis Polyzotis, Sudip Roy, Steven Whang, Martin Zinkevich

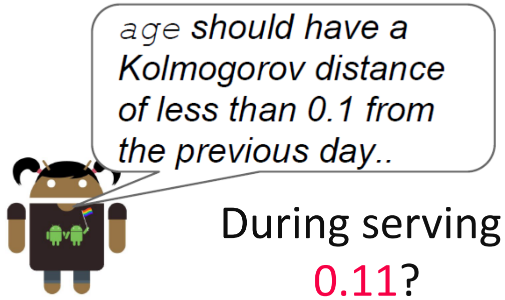
- **Goals:** Robustness (e.g., data, latency) and **model accuracy**

[Neoklis Polyzotis, Sudip Roy, Steven Whang, Martin Zinkevich: Data Management Challenges in Production Machine Learning, **SIGMOD 2017**]

- **#1 Check Deviations Training/Serving Data**
  - Different data distributions, distinct items → impact on model accuracy?

  → See **09 Data Acquisition and Preparation** (Data Validation)

- **#2 Definition of Alerts**
  - Understandable and actionable
  - Sensitivity for alerts (**ignored if too frequent**)


`age` should have a Kolmogorov distance of less than 0.1 from the previous day..

During serving: 0.11?

- **#3 Data Fixes**
  - Identify problematic parts
  - Impact of fix on accuracy
  - How to backfill into training data

"The question is not whether something is 'wrong'. The question is whether it gets fixed"

Monitoring Deployed Models, cont.

Google
Data Management Challenges in Production Machine Learning
Neoklis Polyzotis, Sudip Roy, Steven Whang, Martin Zinkevich

[Neoklis Polyzotis, Sudip Roy, Steven Whang, Martin Zinkevich: Data Management Challenges in Production Machine Learning, **SIGMOD 2017**]

- **Alert Guidelines**
  - **Make them actionable**
    missing field,
    field has new values,
    distribution changes
    less actionable
  - **Question** data AND constraints
  - Combining repairs:
    principle of minimality

[George Beskales et al: On the relative trust between inconsistent data and inaccurate constraints. **ICDE 2013**]

Qualitative Data Cleaning
Xu Chu Ihab Ilyas
Waterloo

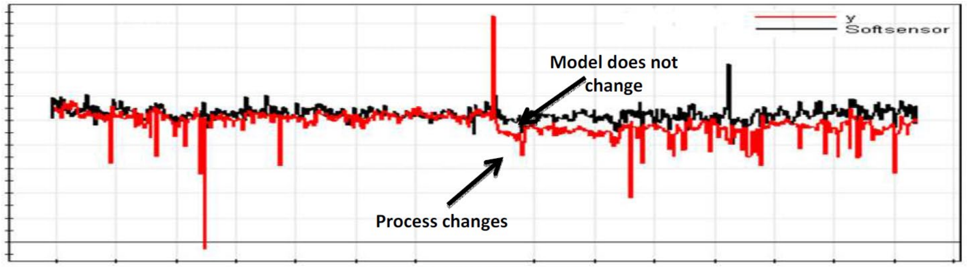
[Xu Chu, Ihab F. Ilyas: Qualitative Data Cleaning. Tutorial, **PVLDB 2016**]

- **Complex Data Lifecycle**
  - Adding new features to production ML pipelines is a **complex process**
  - Data does not live in a DBMS; data often resides in **multiple storage systems** that have **different characteristics**
  - Collecting data for training can be **hard and expensive**

Concept Drift

[A. Bifet, J. Gama, M. Pechenizkiy, I. Žliobaitė: Handling Concept Drift: Importance, Challenges & Solutions, **PAKDD 2011**]

- **Recap Concept Drift** (features → labels)
  - Change of statistical properties / dependencies (features-labels)
  - Requires re-training, parametric approaches for deciding when to retrain
- **#1 Input Data Changes**
  - Population change (gradual/sudden), but also new categories, data errors
  - Covariance shift p(x) with constant p(y|x)
- **#2 Output Data Changes**
  - Label shift p(y)
  - Constant conditional feature distributed p(x|y)



source: Evonik Industries

- **Goals:** Fast adaptation; noise vs change, recurring contexts, small overhead

Concept Drift, cont.

[A. Bifet, J. Gama, M. Pechenizkiy, I. Žliobaitė: Handling Concept Drift: Importance, Challenges & Solutions, **PAKDD 2011**]

- Approach 1: **Periodic Re-Training**
  - Training: **window of latest data** + data selection/weighting
  - Alternatives: incremental maintenance, warm starting, online learning

- Approach 2: **Event-based Re-Training**
  - **Change detection** (supervised, unsupervised)
  - Often model-dependent, specific techniques for time series
  - **Drift Detection Method:** binomial distribution, if error outside scaled standard-deviation → raise warnings and alters
  - **Adaptive Windowing (ADWIN):** window W, append data to W, drop old values until avg windows W=W1-W2 similar (below epsillon), raise alerts
  - **Kolmogorov-Smirnov distance / Chi-Squared:** univariate statistical tests training/serving

[Albert Bifet, Ricard Gavaldà: Learning from Time-Changing Data with Adaptive Windowing. **SDM 2007**]

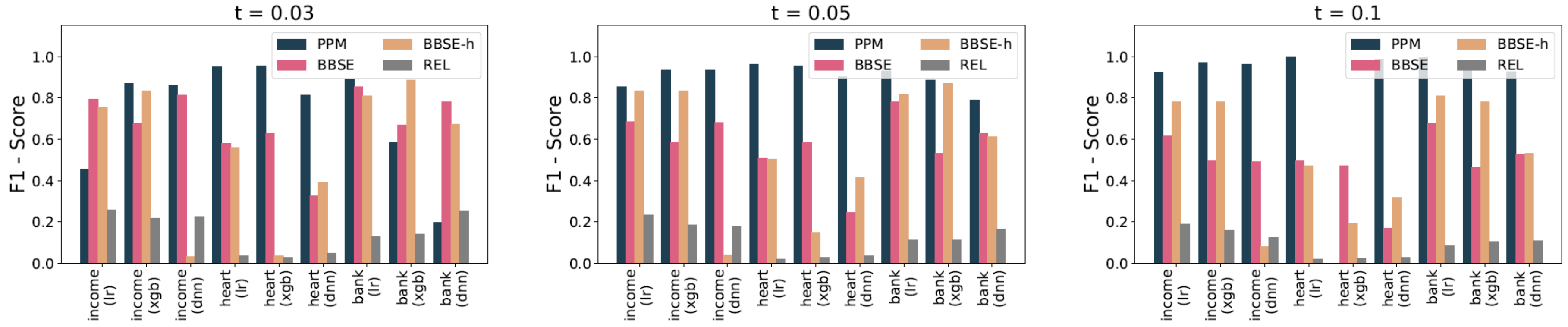
[https://scikitmultiflow.readthedocs.io/en/stable/api/generated/skmultiflow.drift_detection.ADWIN.html]

Concept Drift, cont.

[Sebastian Schelter, Tammo Rukat, Felix Bießmann: Learning to Validate the Predictions of Black Box Classifiers on Unseen Data. **SIGMOD 2020**]

- **Model-agnostic Performance Predictor**
  - Approach 2: Event-based Re-Training
  - User-defined error generators
  - Synthetic data corruption → impact on black-box model
  - Train performance predictor (regression/classification at threshold t) for expected prediction quality on **percentiles of target variable ŷ**

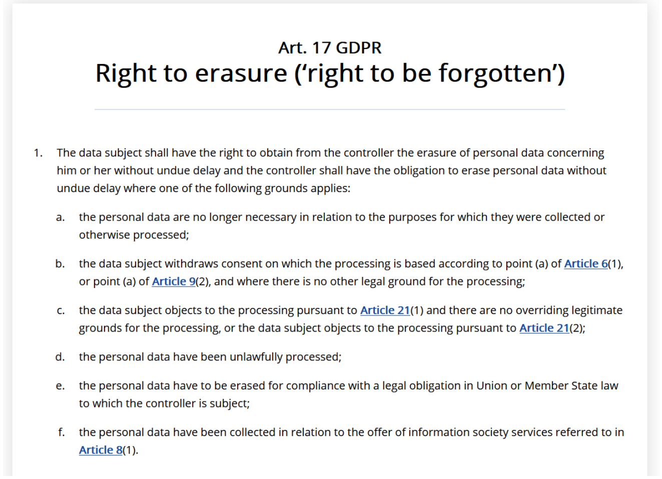
- **Results PPM**



GDPR (General Data Protection Regulation)

- **GDPR "Right to be Forgotten"**
  - Recent laws such as GDPR require companies and institutions to **delete user data upon request**
  - Personal data must not only be deleted from primary data stores but also from **ML models** trained on it (Recital 75)

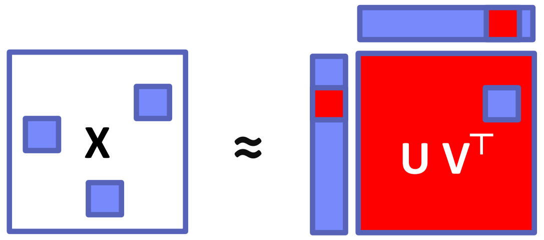
  [https://gdpr.eu/article-17-right-to-be-forgotten/]



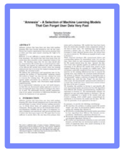
Art. 17 GDPR
Right to erasure ('right to be forgotten')

1. The data subject shall have the right to obtain from the controller the erasure of personal data concerning him or her without undue delay and the controller shall have the obligation to erase personal data without undue delay where one of the following grounds applies:
   a. the personal data are no longer necessary in relation to the purposes for which they were collected or otherwise processed;
   b. the data subject withdraws consent on which the processing is based according to point (a) of Article 6(1), or point (a) of Article 9(2), and where there is no other legal ground for the processing;
   c. the data subject objects to the processing pursuant to Article 21(1) and there are no overriding legitimate grounds for the processing, or the data subject objects to the processing pursuant to Article 21(2);
   d. the personal data have been unlawfully processed;
   e. the personal data have to be erased for compliance with a legal obligation in Union or Member State law to which the controller is subject;
   f. the personal data have been collected in relation to the offer of information society services referred to in Article 8(1).

- **Example Deanonymization**
  - Recommender systems: models **retain user similarly**
  - Social network data / clustering / KNN
  - Large language models (e.g., GPT-3)



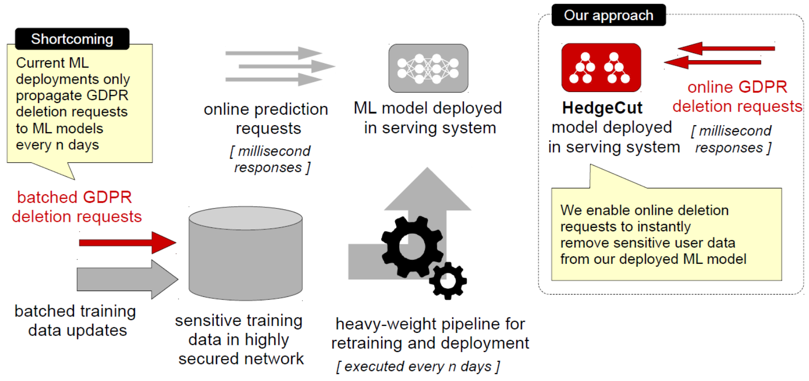
[Sebastian Schelter: "Amnesia" - Machine Learning Models That Can Forget User Data Very Fast. **CIDR 2020**]



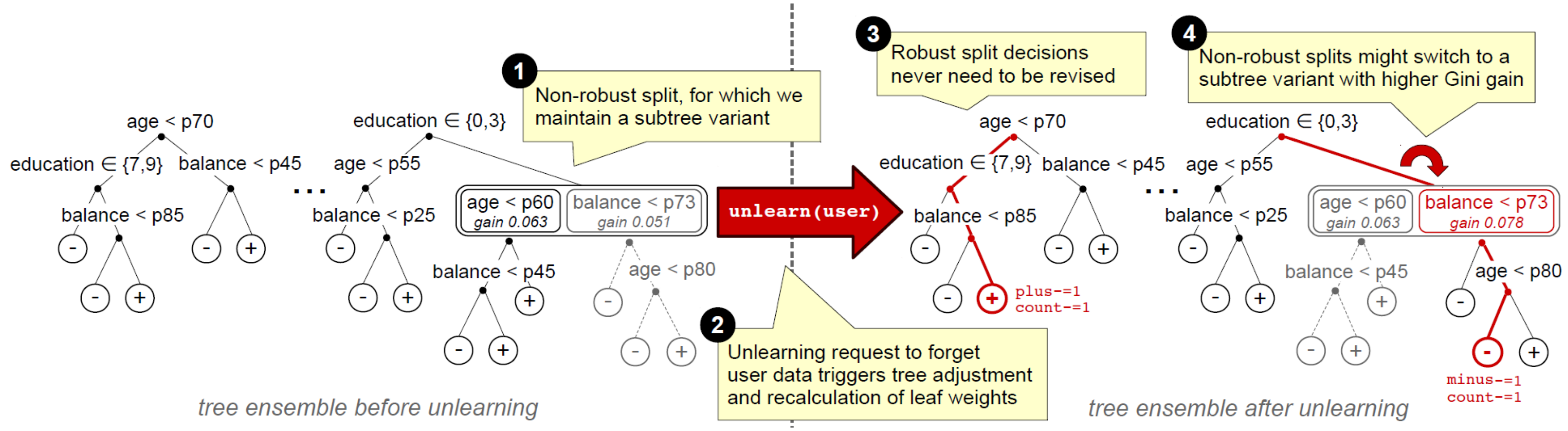
GDPR, cont.

[Sebastian Schelter, Stefan Grafberger, Ted Dunning: HedgeCut: Maintaining Randomised Trees for Low-Latency Machine Unlearning, **SIGMOD 2021**]

- **HedgeCut Overview**
  - Extremely Randomized Trees (ERT): ensemble of DTs w/ randomized attributes and cut-off points
  - Online unlearning requests < 1ms w/o retraining for few points


Shortcoming
Current ML deployments only propagate GDPR deletion requests to ML models every n days
online prediction requests
[millisecond responses]
ML model deployed in serving system
batched GDPR deletion requests
batched training data updates
sensitive training data in highly secured network
heavy-weight pipeline for retraining and deployment
[executed every n days]
Our approach
HedgeCut model deployed in serving system
online GDPR deletion requests
[millisecond responses]
We enable online deletion requests to instantly remove sensitive user data from our deployed ML model

- **Handling of Non-robust Splits**


1 Non-robust split, for which we maintain a subtree variant
age < p70
education ∈ {7,9}
balance < p45
balance < p85
education ∈ {0,3}
age < p55
balance < p25
age < p60 gain 0.063
balance < p73 gain 0.051
balance < p45
age < p80
unlearn(user)
2 Unlearning request to forget user data triggers tree adjustment and recalculation of leaf weights
3 Robust split decisions never need to be revised
4 Non-robust splits might switch to a subtree variant with higher Gini gain
balance < p73 gain 0.078
plus-=1 count-=1
minus-=1 count-=1
tree ensemble before unlearning
tree ensemble after unlearning

Summary and Q&A

- **Model Exchange and Serving**
- **Model Monitoring and Updates**

- **Tomorrow's Lectures**
  - **05 Compilation and Optimization Techniques** [Aug 30, 8am]
  - **06 Execution and Parallelization Strategies** [Aug 30, 10.15am]
  - **07 HW Accelerators and Data Access Methods** [Aug 30, 12.45am]
  - **Discussion/Implementation Programming Projects** [Aug 30, 3pm]