

# Evolution of software for data processing and analysis

#### Andrey Ustyuzhanin NRU Higher School of Economics Yandex School of Data Analysis ICL





# Evolution of Science (abridged)

- 1000+ years Empirical (Aristotle, Democritus, ) 100+ years – theoretical (Newton, Kepler, ) 50+ years – computational (John von Neumann) 10+ years – data-driven science (the "Fourth paraditm", Jim Gray) Unify theory, experiment and simulation
- Data is captured or simulated
- Data is processed and analysed by software
- Information/knowledge is stored in computer
- Scientists analyzes database/files using data management and statistics Less than 10 years – community-driven trend (open science, crowd-science)



### Particle Physics is heavily data-driven

Data processing

- High-level triggers
- Tracking
- Particle Identification >
- **Event Reconstruction**
- Signal/background separation

Simulation

- Pythia tuning
- GEANT speed-up

Detector optimization ("bang per bucks")

Sensitivity / resolution

Cost



## Quick self-intro

Head of LHCb team in Yandex School of Data Analysis (YSDA) Head of Laboratory (link) at Higher School of Economics (HSE), YSDA (since 2007):

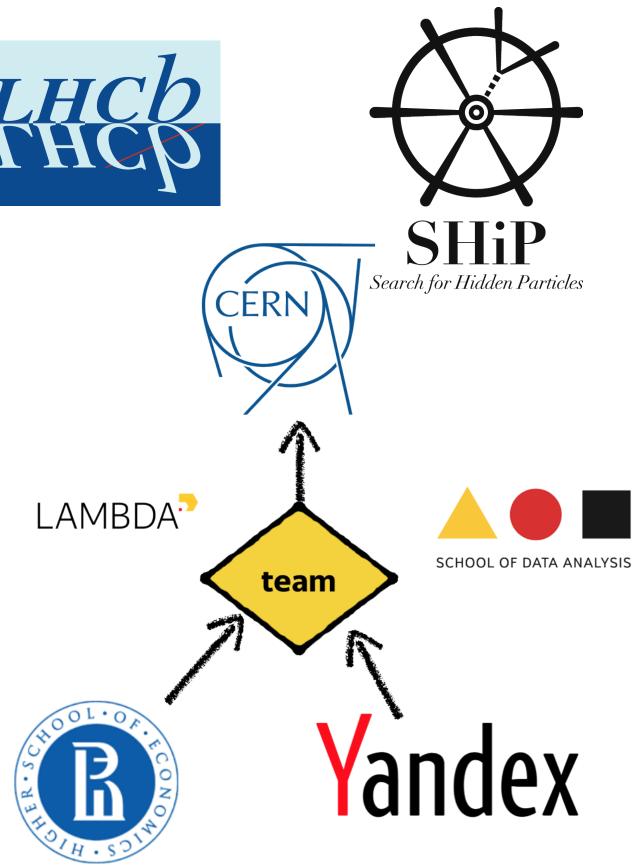
- Joint master's degree in data science
- Solving High Energy Physics problems with ML approaches
- member of LHCb, SHiP, CRAYFIS

HSE, Laboratory (since 2015):

- focuses on applying ML to natural science challenges
- HSE has joined LHCb this summer!

Collaborates with industry as well

Education activities (MLHEP, ML at ICL, ClermonFerrand, LaSAL, Coursera)





# Machine Learning very quick intro (simplified)

#### Machine Learning core idea:

with data, without being explicitly programmed;

#### Data Science:

for knowledge extraction from the raw data;

Datasets: digital (simplified) representation of our world; Popular problem categories: supervised, unsupervised, reinforcement; Metric – proxy of a quality we can expect from such an algorithm; Optimization methods + learning theory: to reach prediction error minima fast; Boosted by a) computing power, b) huge datasets (images, texts, speech, etc.)

Field of computer science that uses statistical techniques to give computers the ability to "learn" (i.e. progressively improve performance on a specific task)

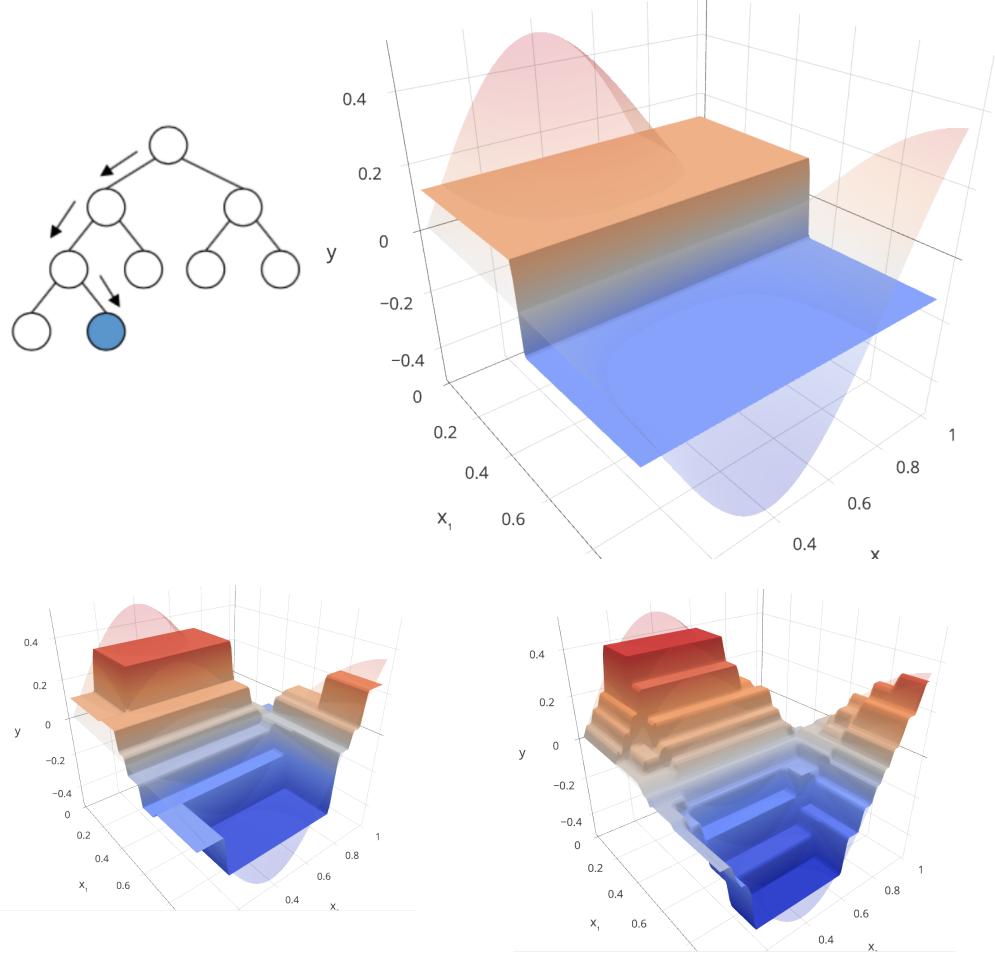
Interdisciplinary branch of science with focus on tools and methods suitable





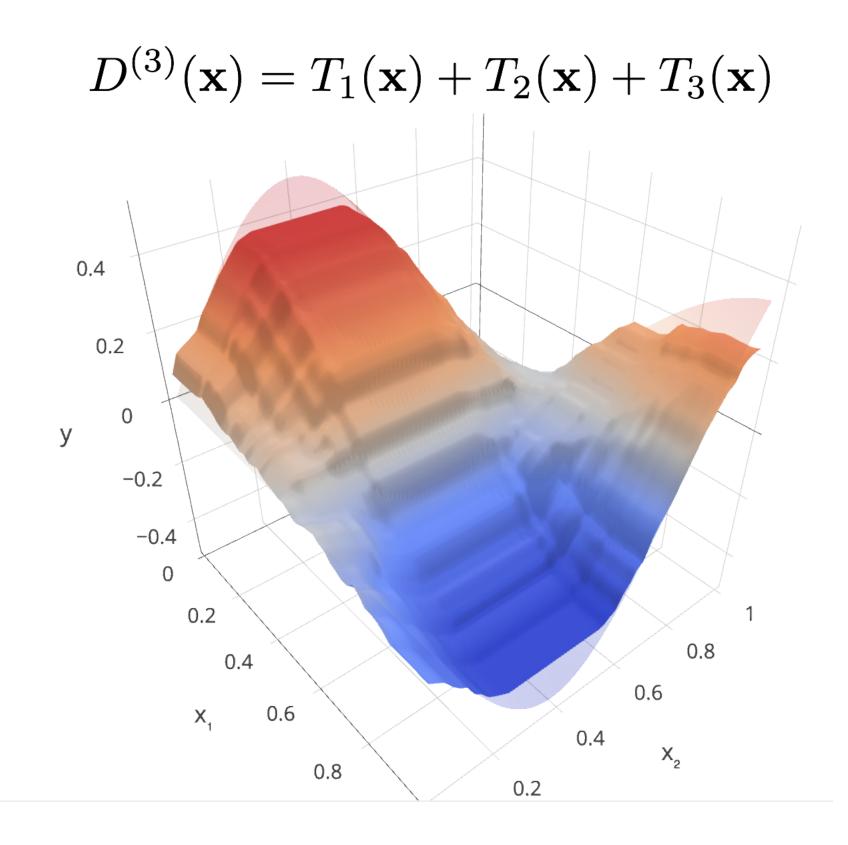
### An example – boosting over decision trees

Decision tree (depth in [1, 4, 6])



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Tree ensemble (Boosted Decision Trees)



$$T_4(\mathbf{x}) \leftarrow \alpha(f(\mathbf{x}) - D^3(\mathbf{x}))$$

http://bit.ly/2mtVewf





## Machine Learning history (abridged)

Has passed several development stages since 1950-s

- Expert systems
- Knowledge representations
- Connectioninst systems (backpropagation)
- Data mining

Has been adopted by several branches of domain sciences (including Physics) Boosted by deep learning in 2010-s field – i.e. neural-network-like processing

Relation to statistics: Leo Breiman distinguished two statistical modelling paradigms: data model and algorithmic model, wherein "algorithmic model" means more or less the machine learning algorithms.

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https://wiki2.org/en/Machine\_learning





### Convolutional neural network (NN) for vision

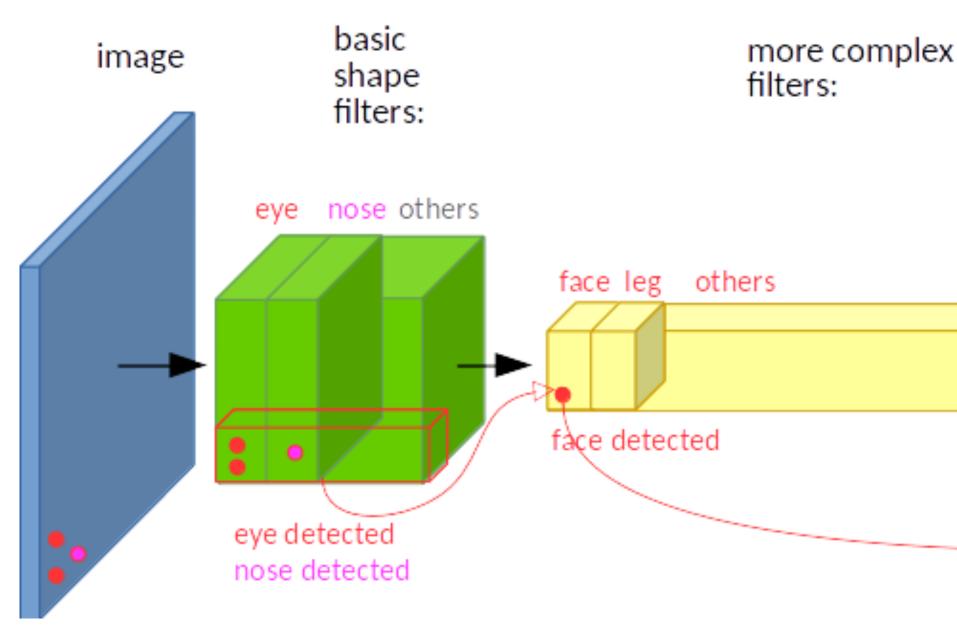
Input Image

1	2	1	3	1
2	1 <b>x 0</b>	1 <b>x 1</b>	2	1
2	1 <b>x 1</b>	1 x 2	1	3
0	1	2	2	1
4	1	3	1	0

#### Feature Map

6	4	8	5
5	4		





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http://bit.ly/2muXG5Z http://bit.ly/2uMSSwl





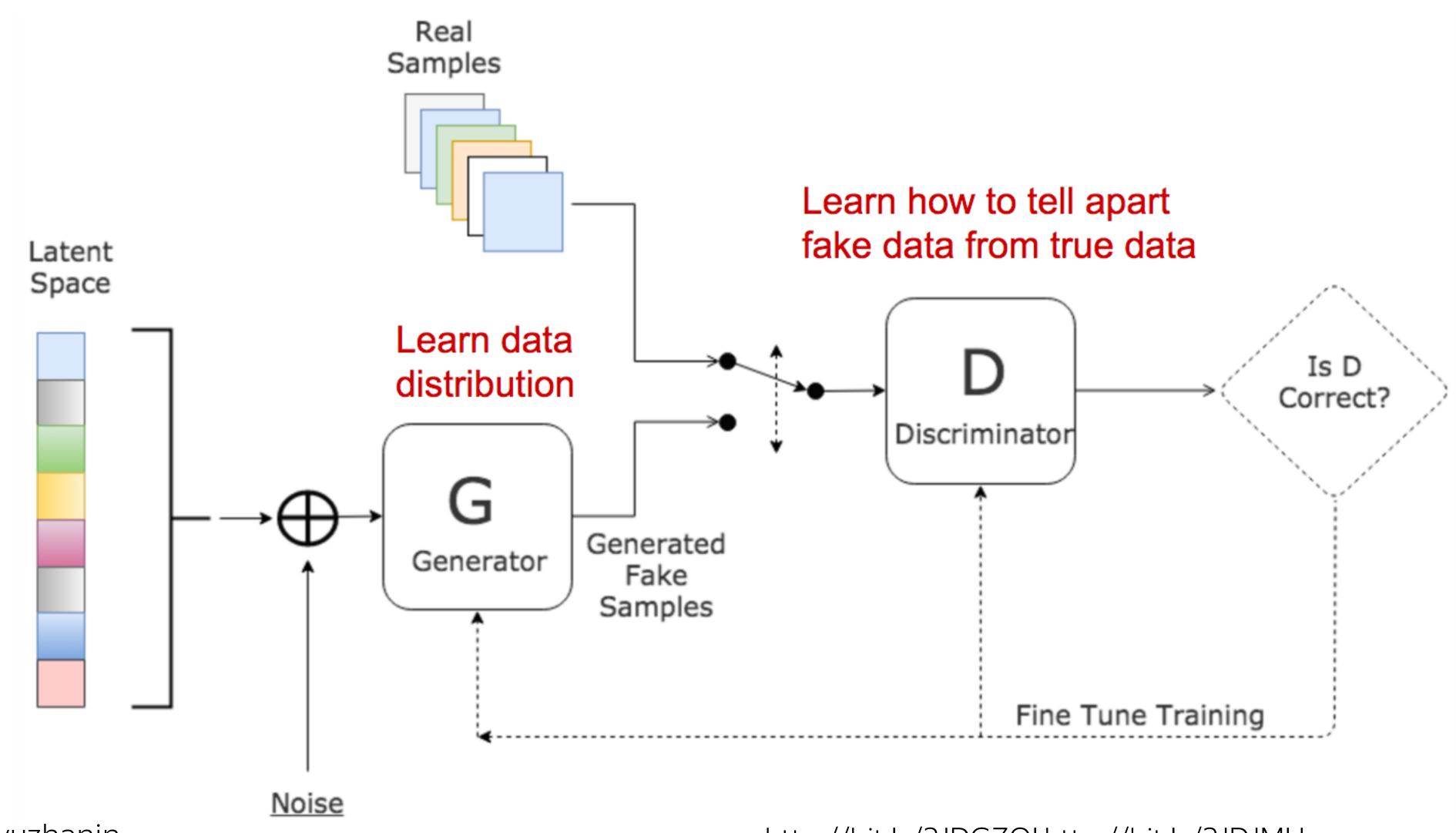
fully-connected layer

> All data transformations are differentiable, so we can use gradient to adjust NN human body coefficients to mimize the detected prediction error





### Generative Adversarial Networks (GAN)



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http://bit.ly/2JDGZOI http://bit.ly/2JDJMHx



# Optimize sophisticated functions

We'd better prepare for the following challenges:

- > Non-smooth or even discontinuous objective
- > Multi-modality (i.e. oscillating wrt features)
- > Noise-resistance
- > High dimensionality, e.g.,  $d \gg 1000$
- Constraints (possibly non-smooth, ...)

Approaches that work:

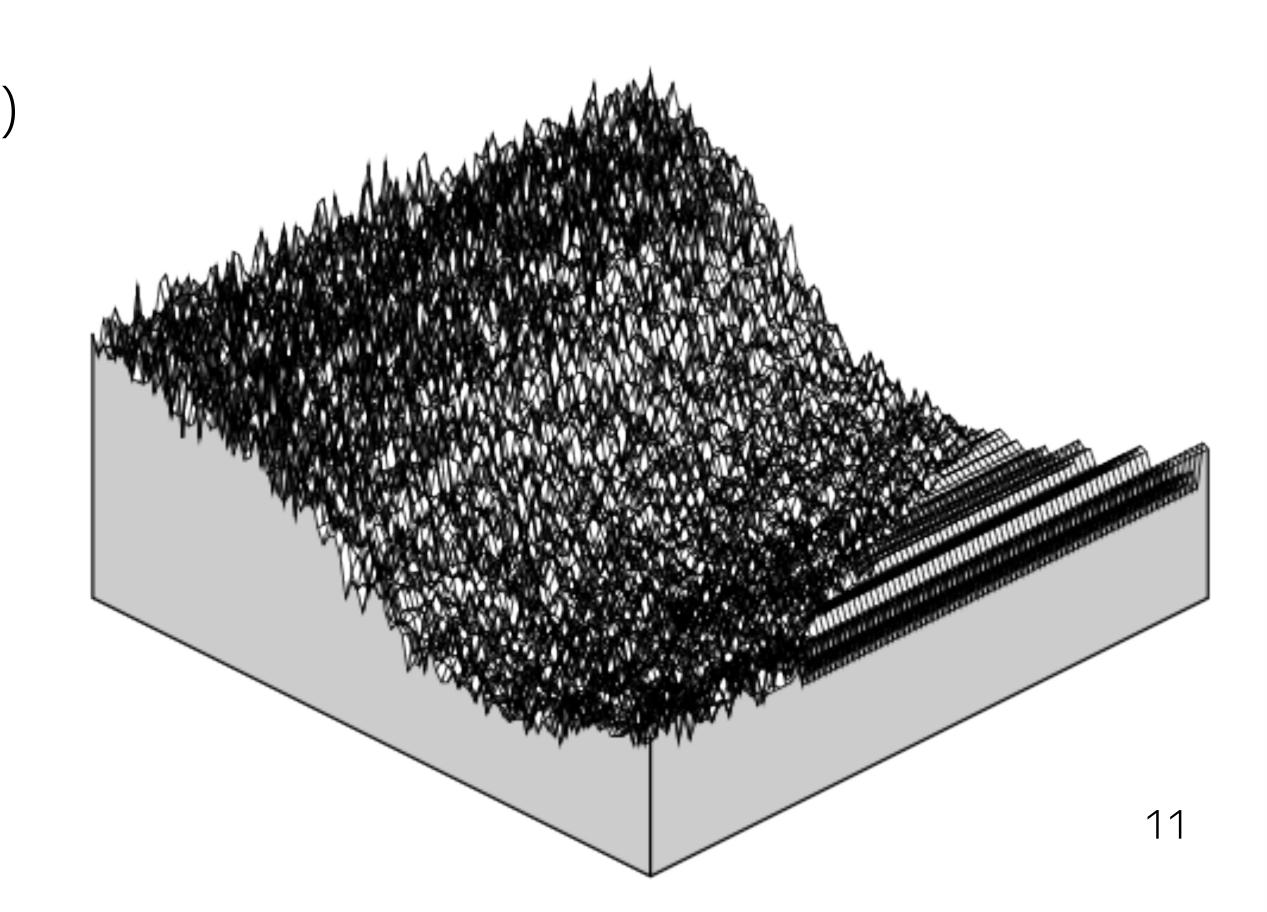
- > Kriging
- > Baeysian optimization
- > Natural evolution strategy

HEP applications:

- > Design of detectors
- > MC generator parameter tuning
- > Planning of experiment

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#### challenges: s objective eatures)



### Deep Learning summary

Versatile way (language) for expres problems, e.g.:

- > Shift-invariance convolutional layer
- Sequence memory for recurrent layer
  Sophisticated optimization methods
  Now driven mainly by industry (Apple, Goole, Facebook, Amazon, Microsoft)
  Is not going away anytime soon
  Prominent challenges:
- > Model Inrepretation
- > Few-shot learning

Versatile way (language) for expressing solution templates for data-driven

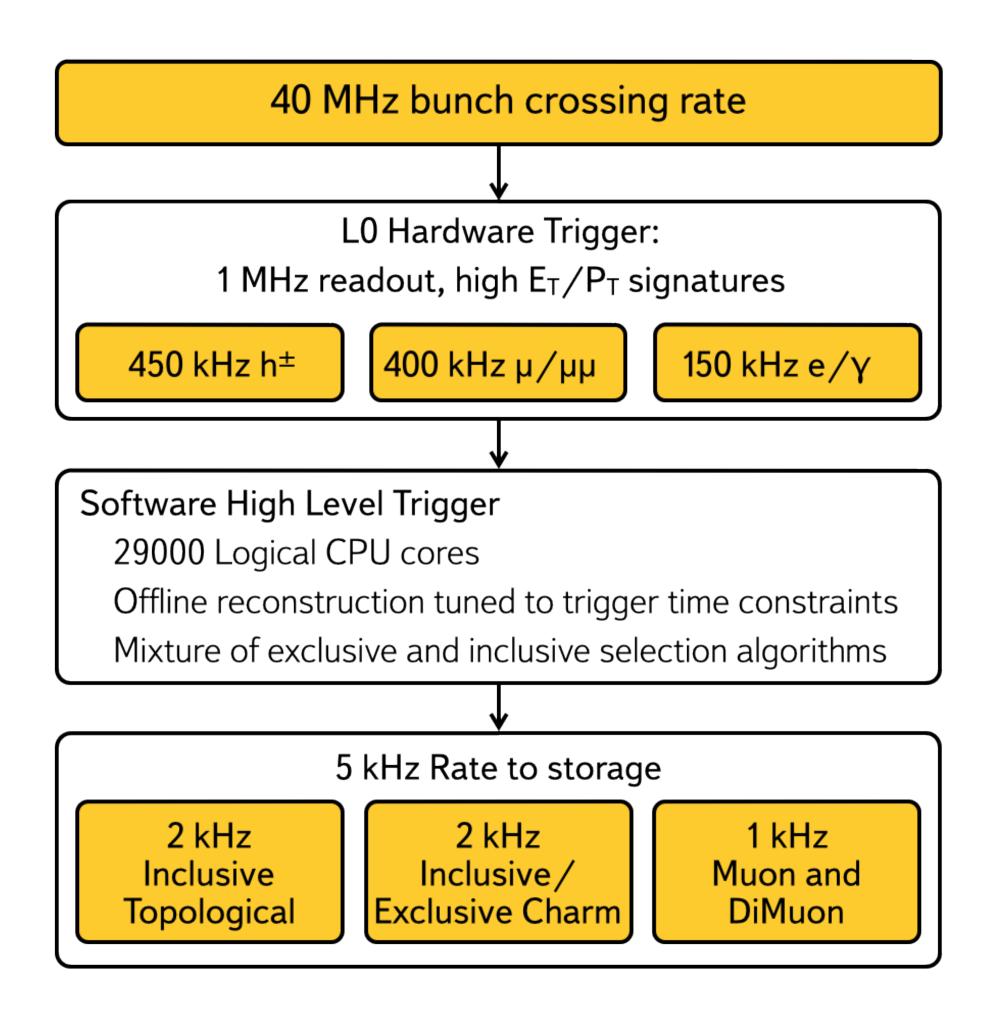


# ML examples in HEP (abridged and heavily biased)



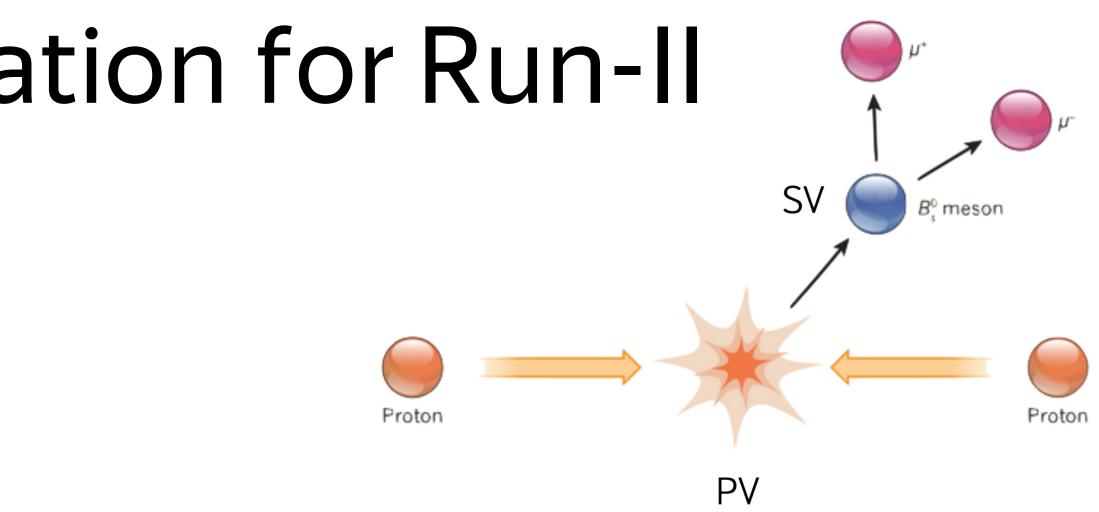


# LHCb Trigger Optimization for Run-II

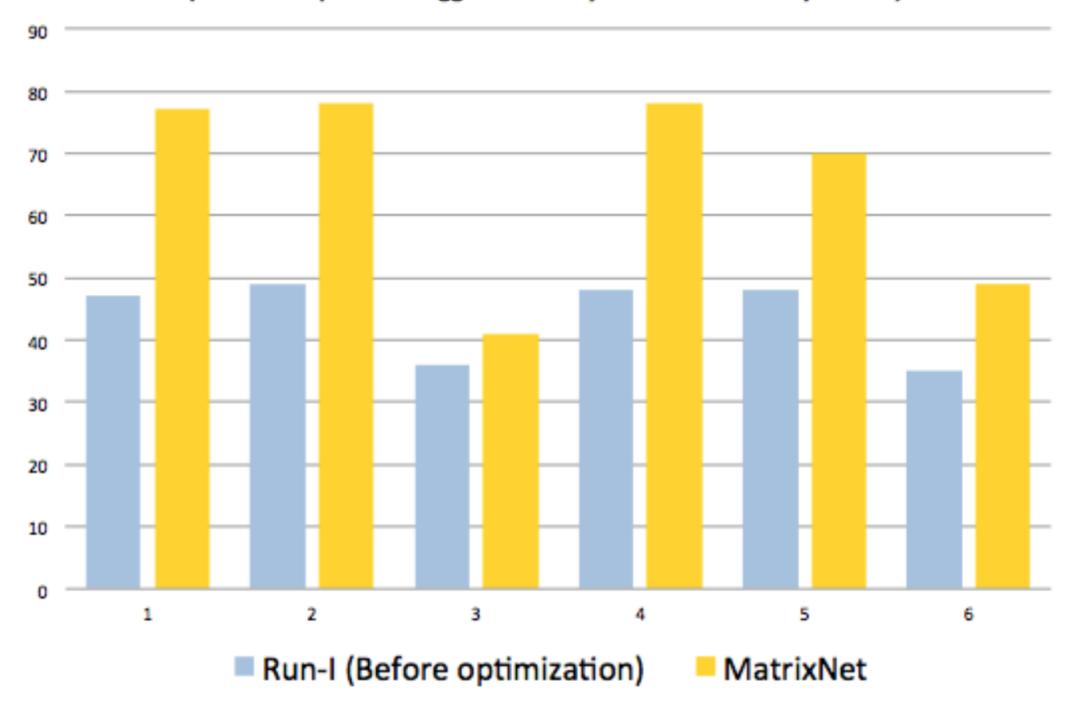


http://stacks.iop.org/1742-6596/664/i=8/a=082025

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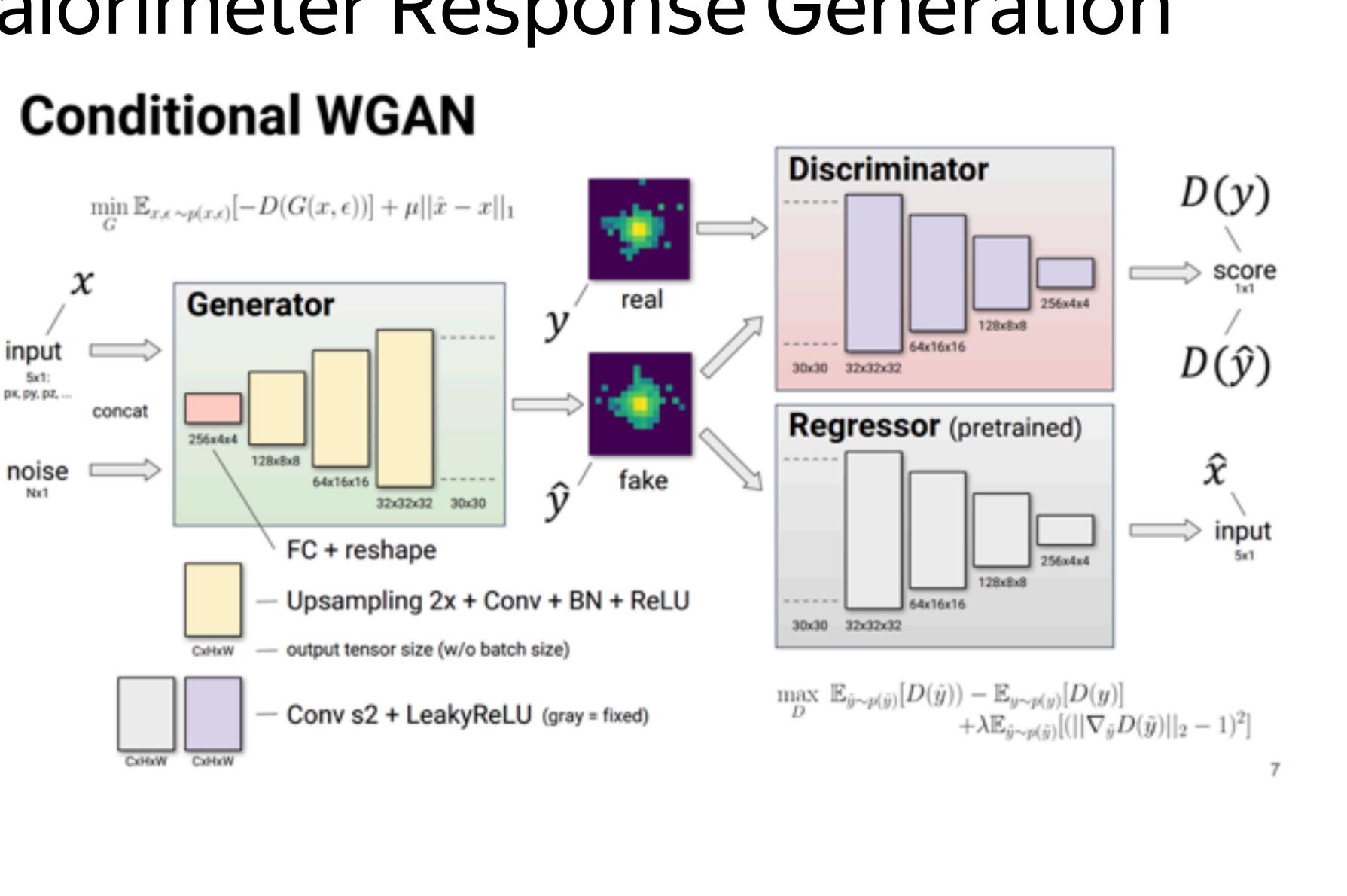
N-Body trigger Performance Comparison (bars correspond to trigger efficiency for different decay modes)





### LHCb Fast Calorimeter Response Generation Conditional WGAN

Goal: approximate **Resource Consuming** simulation by NN trained by WGAN **Demand for** simulation will increase 100x



http://bit.ly/2JDM9tV

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$$\begin{array}{l} \max_{D} \mathbb{E}_{\hat{y} \sim p(\hat{y})}[D(\hat{y})) - \mathbb{E}_{y \sim p(y)}[D(y)] \\ + \lambda \mathbb{E}_{\tilde{y} \sim p(\hat{y})}[(||\nabla_{\tilde{y}}D(\tilde{y})||_{2} - 1)^{2}] \end{array}$$

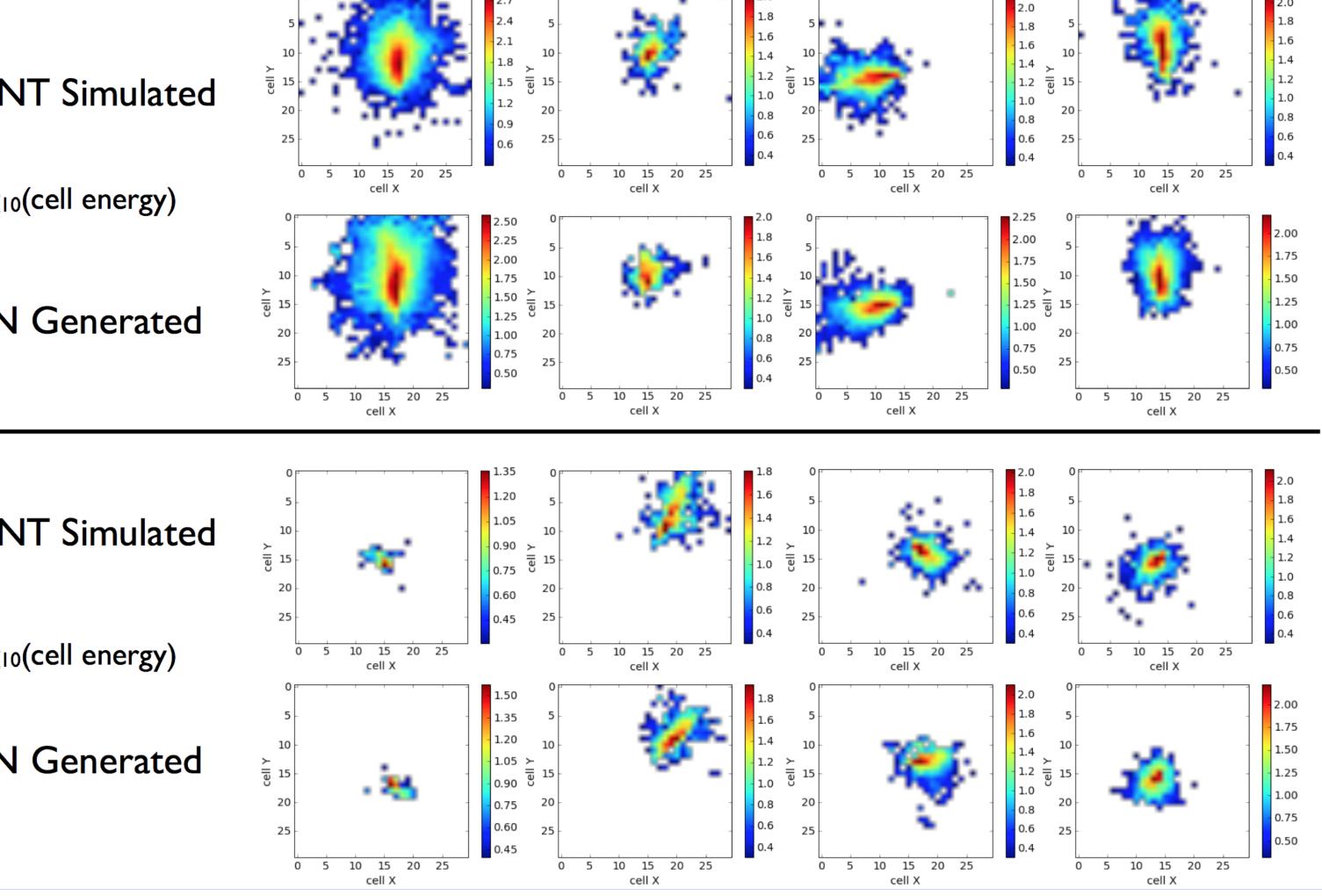
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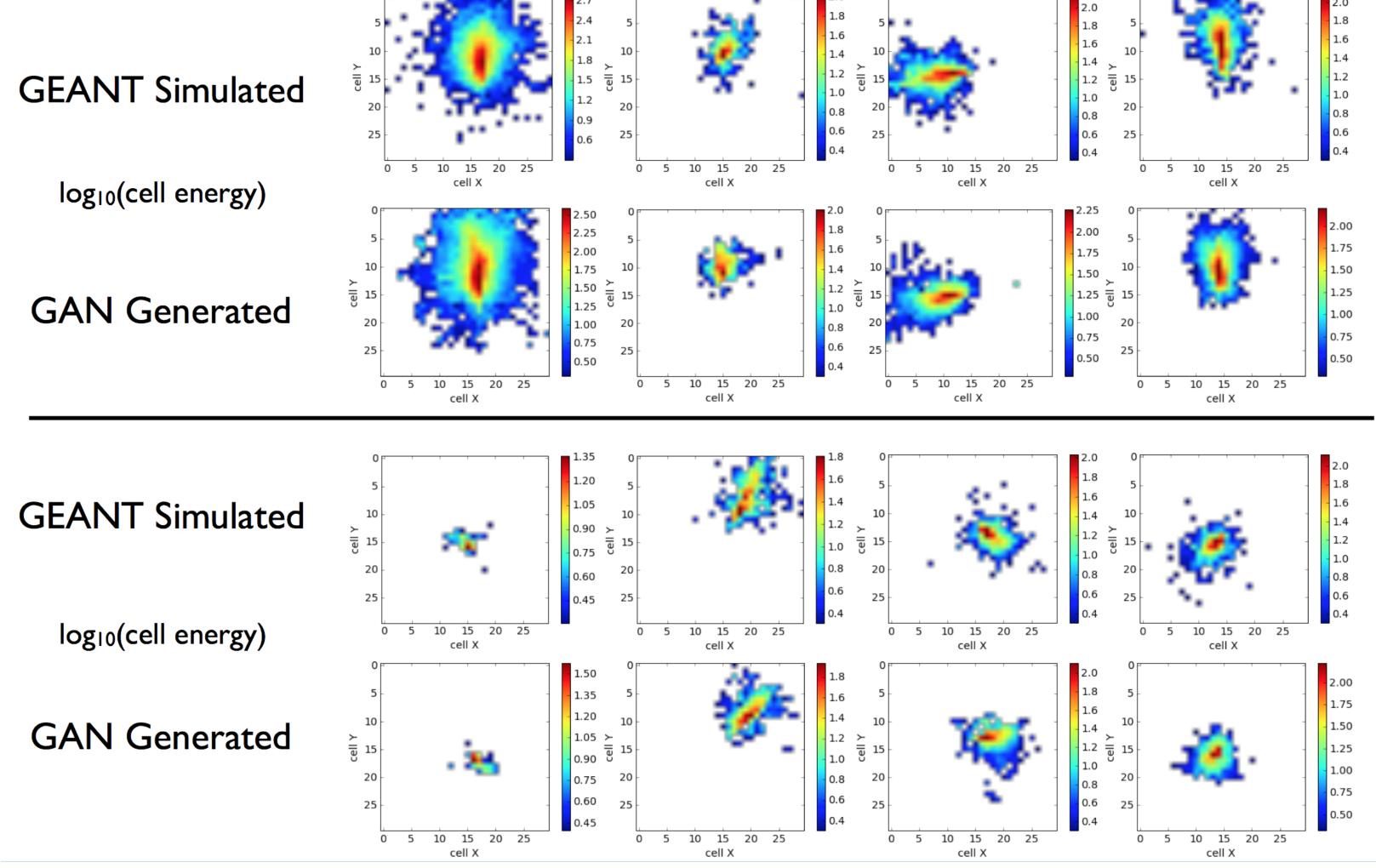
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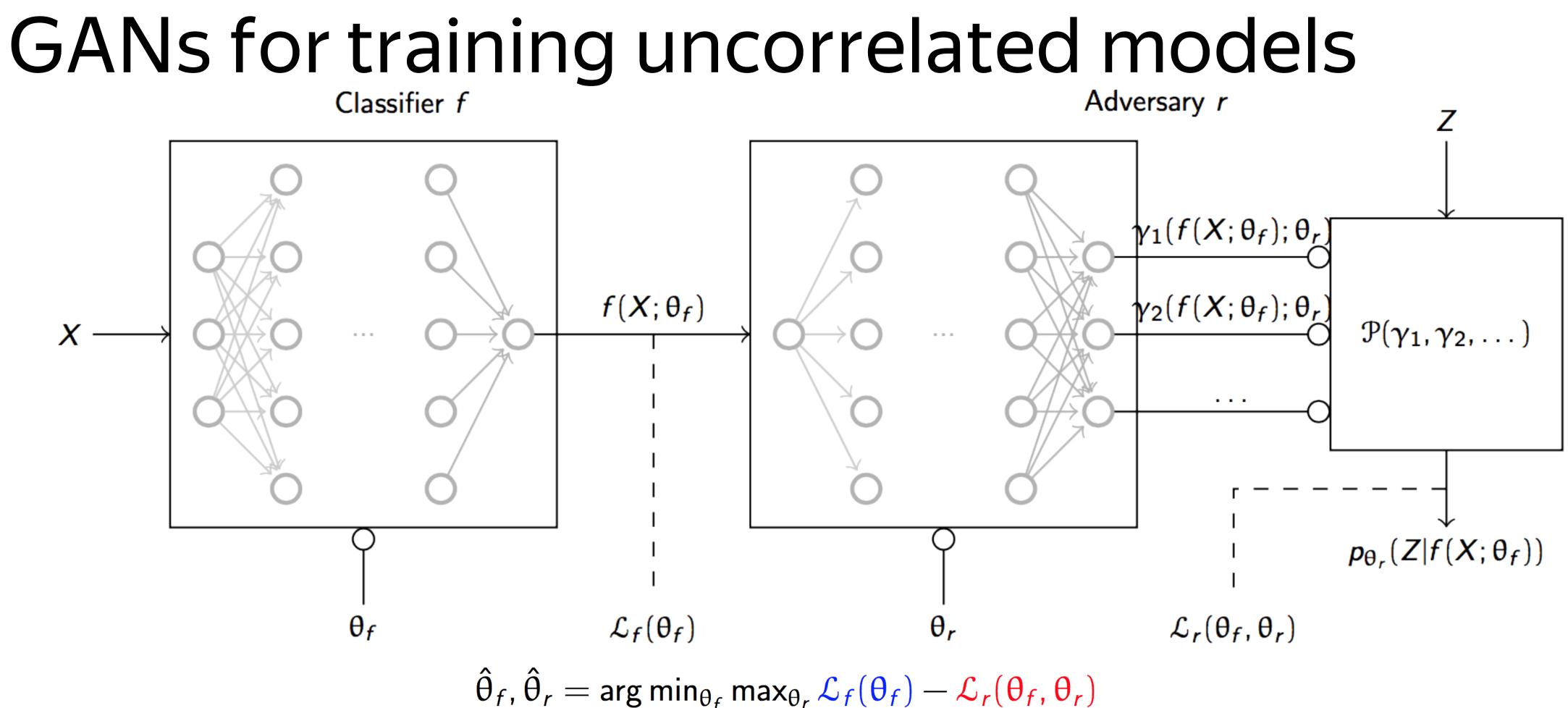
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### Generator in Full 5D





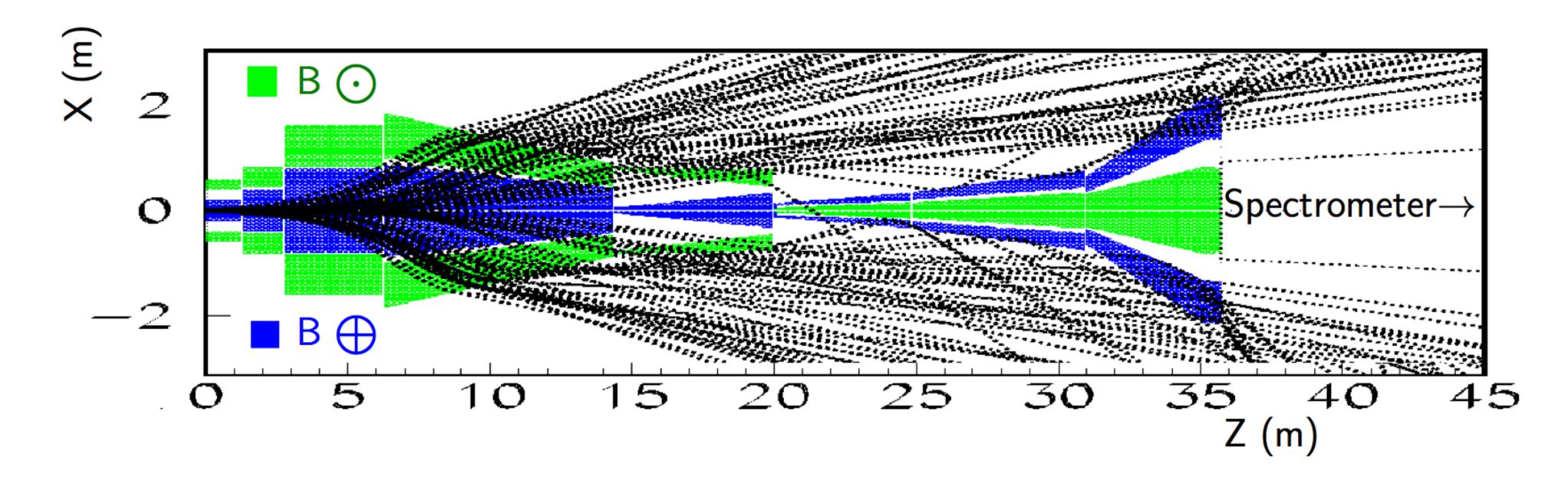
Adversary part identifies PDF parameters that can be used to infer Z (decor. feature) from f. Intuitively, *r* penalizes *f* so it is impossible to reconstruct Z.

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G. Louppe et al, http://bit.ly/2GejPgY



### SHiP Active Muon Shield Optimization



50—dimensional optimization problem

Bayesian optimization: "designed" magnets that have same efficiency by are 25% lighter – converts to 1M CHF

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### http://iopscience.iop.org/article/10.1088/1742-6596/934/1/012050/meta



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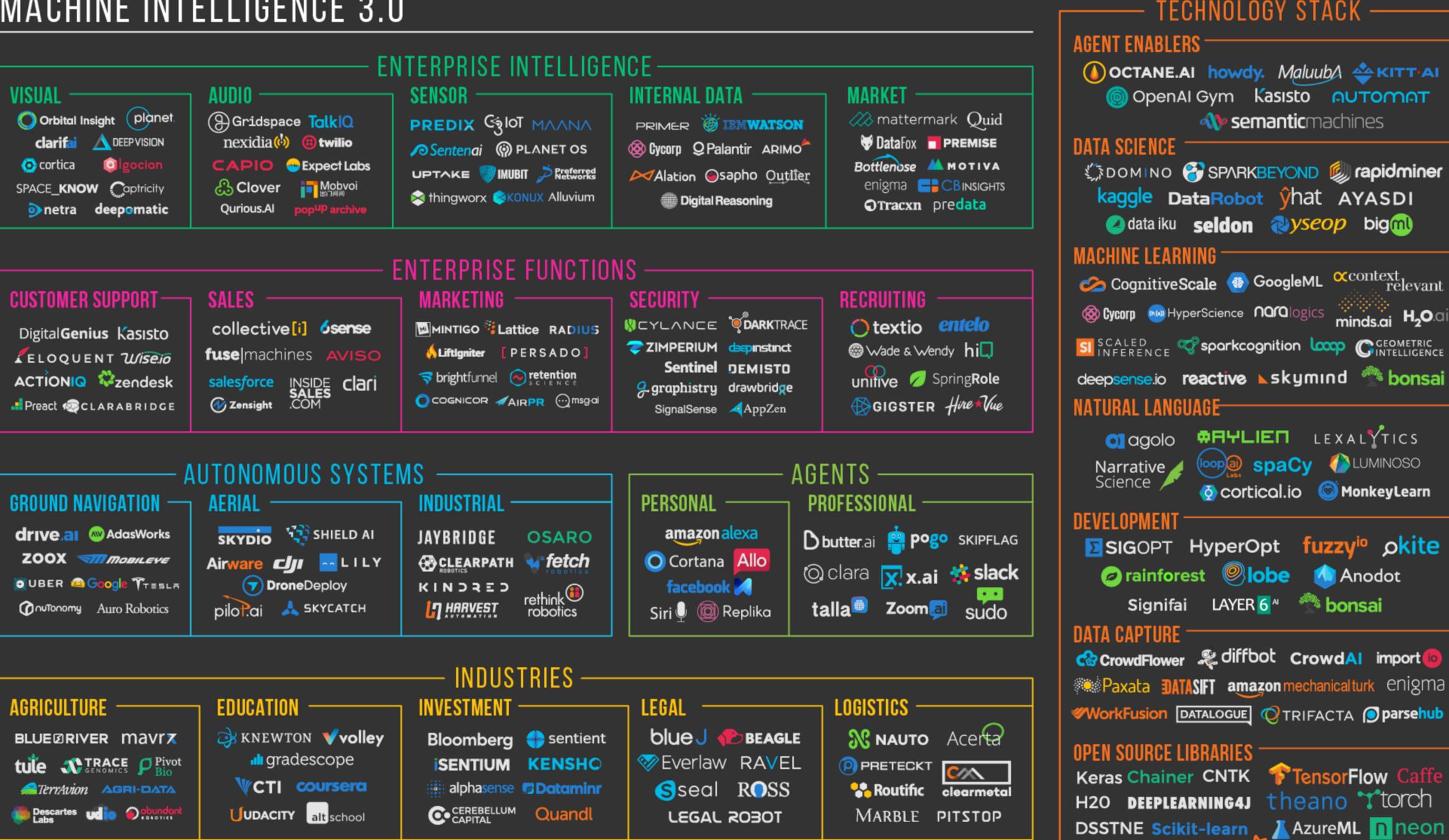
### Industrial ML (abridged)

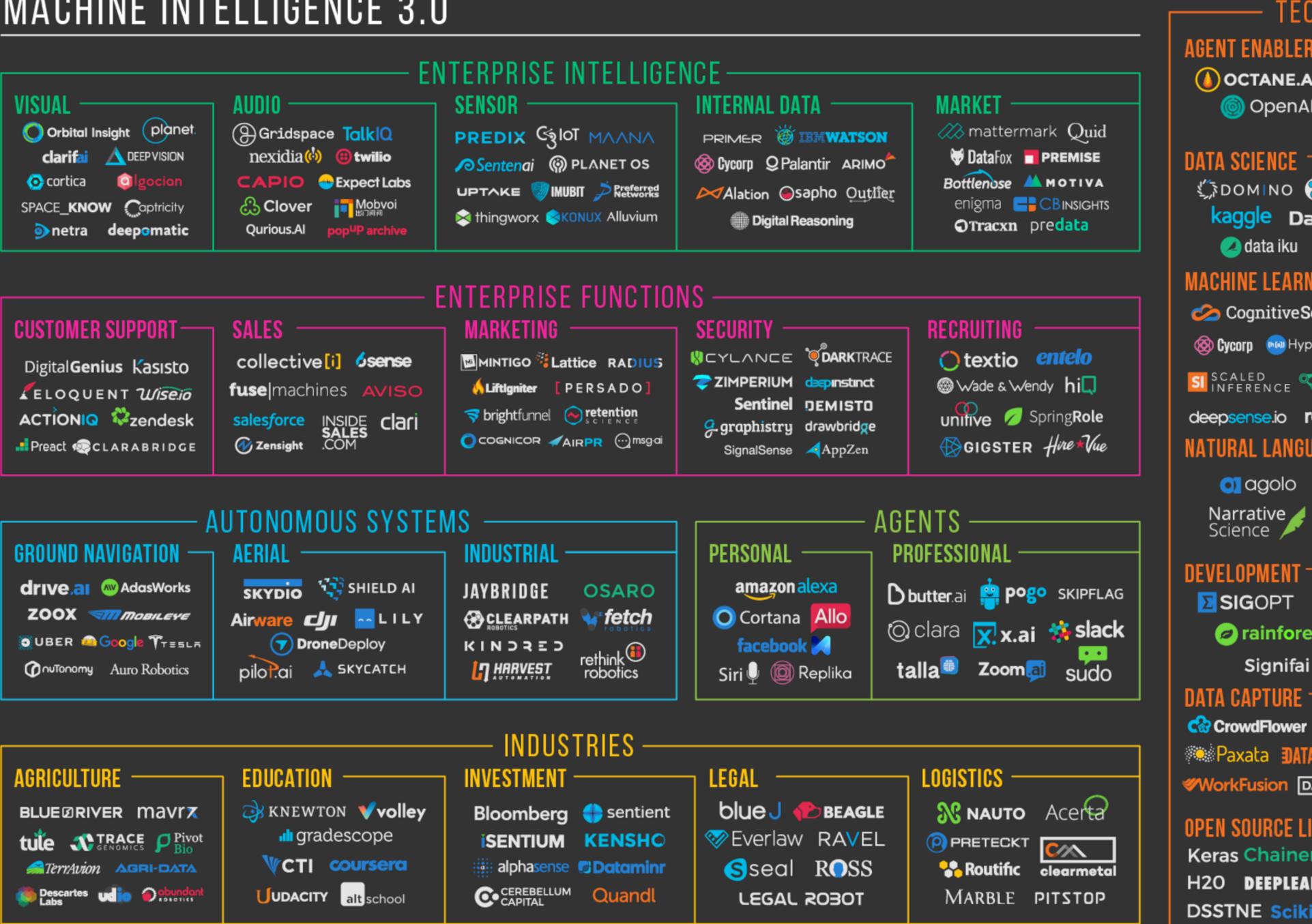


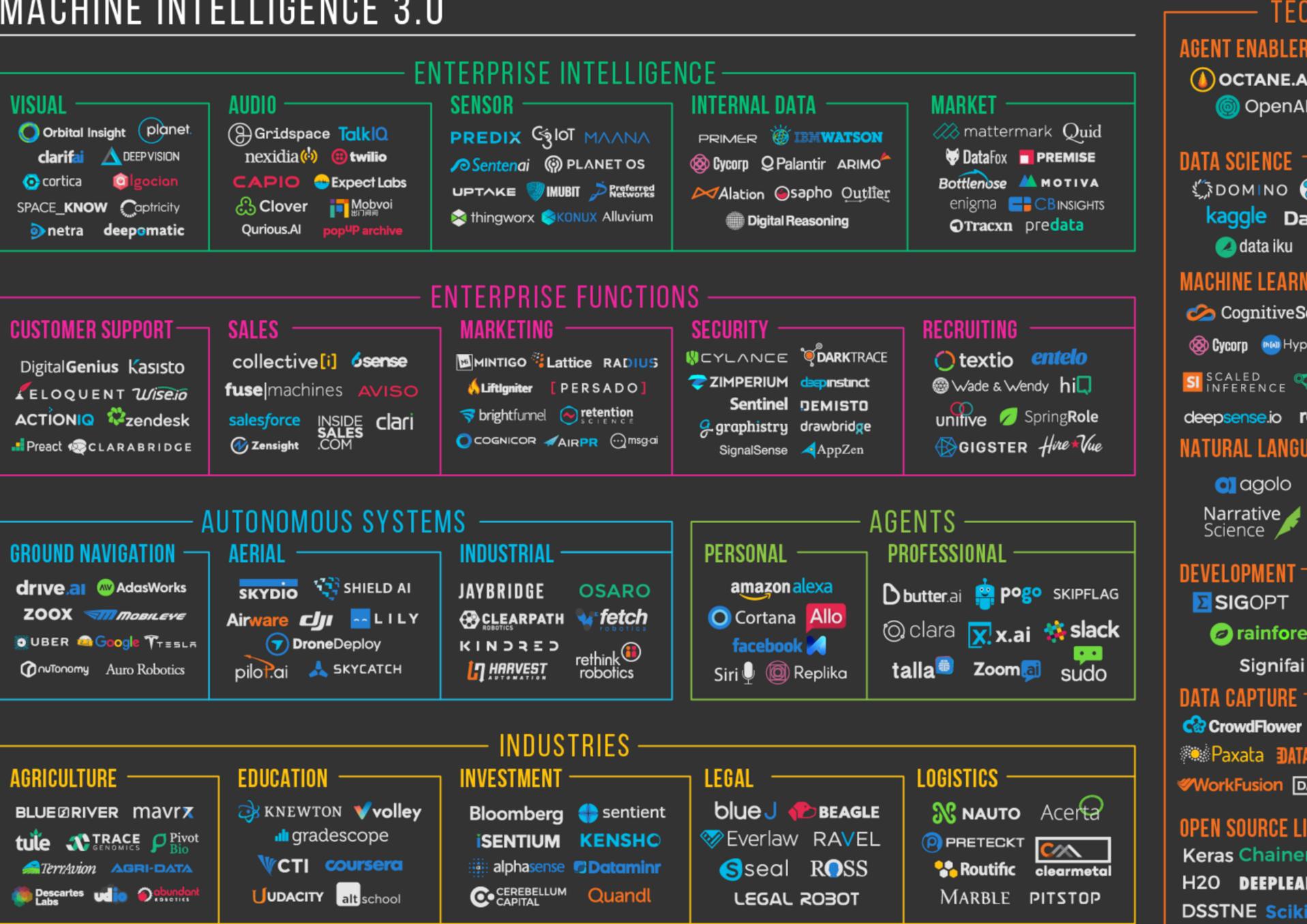


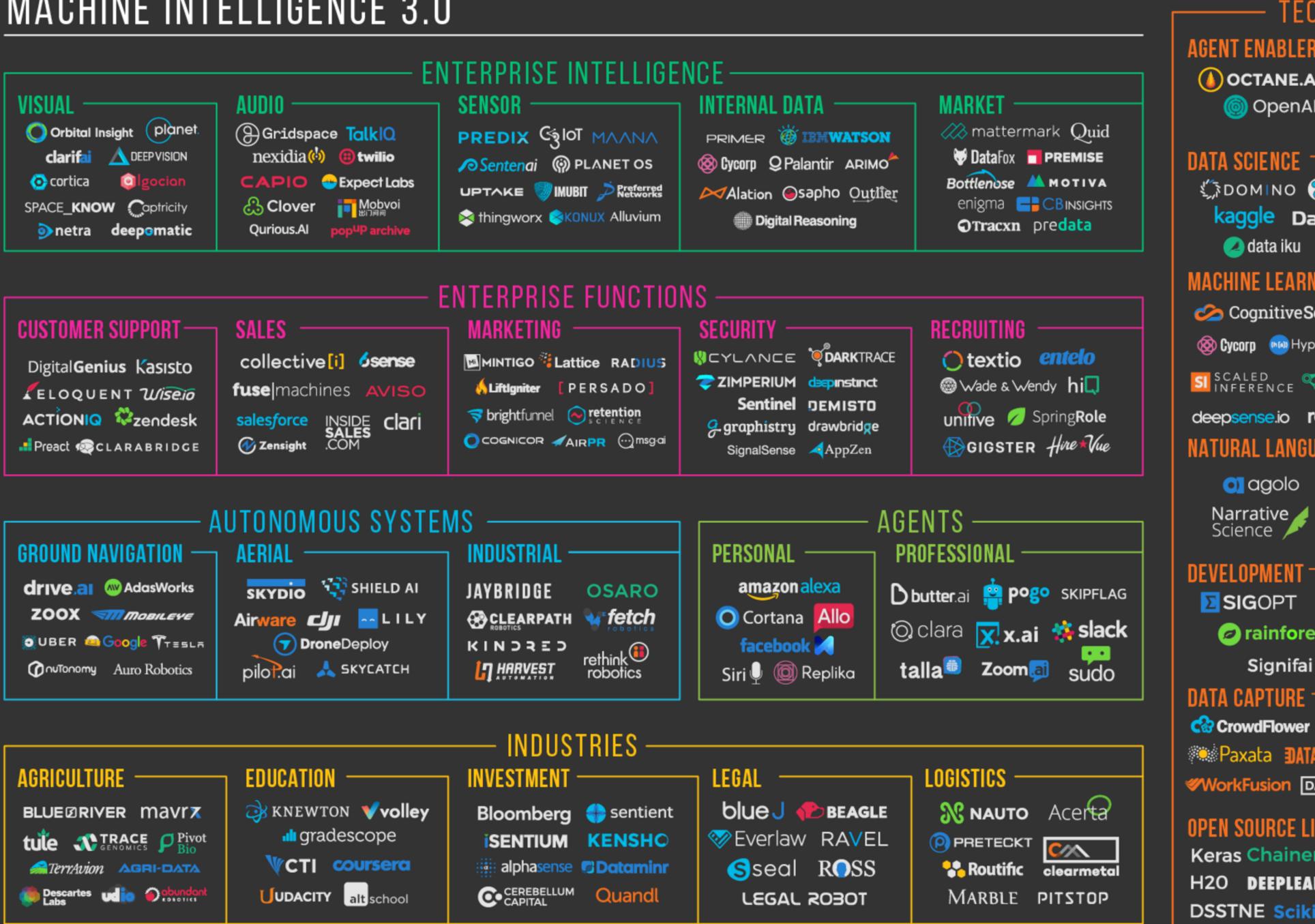


#### MACHINE INTELLIGENCE 3.0

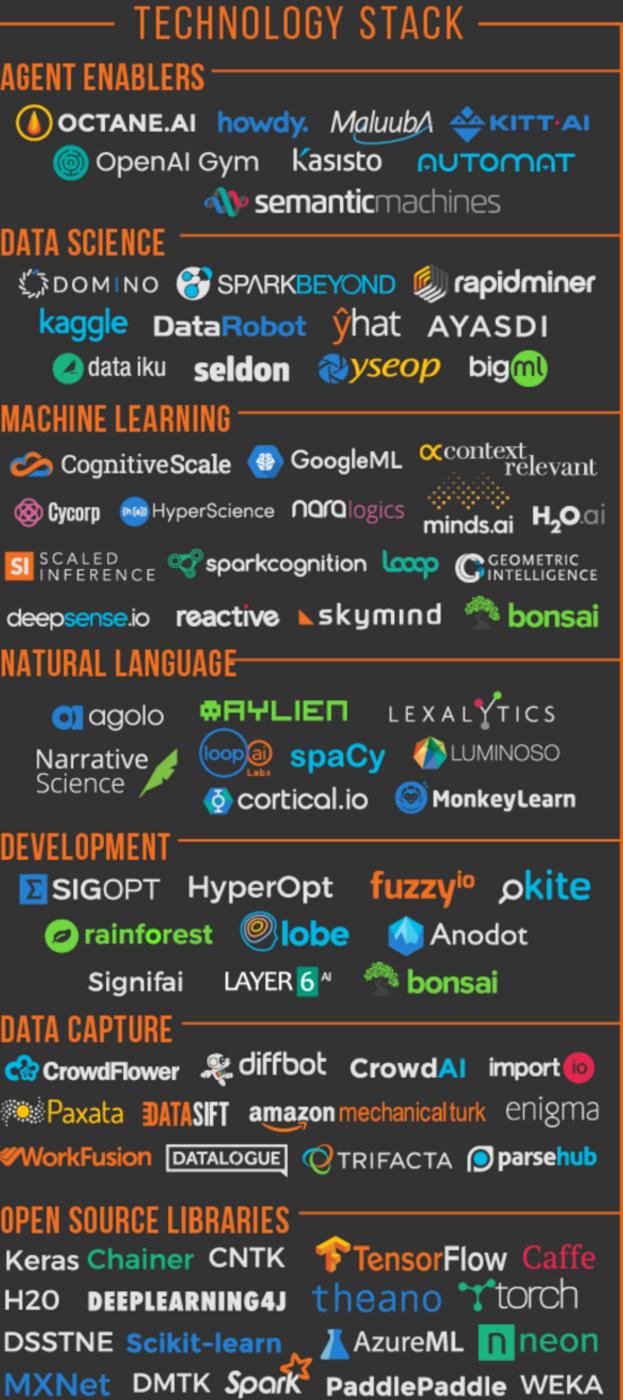




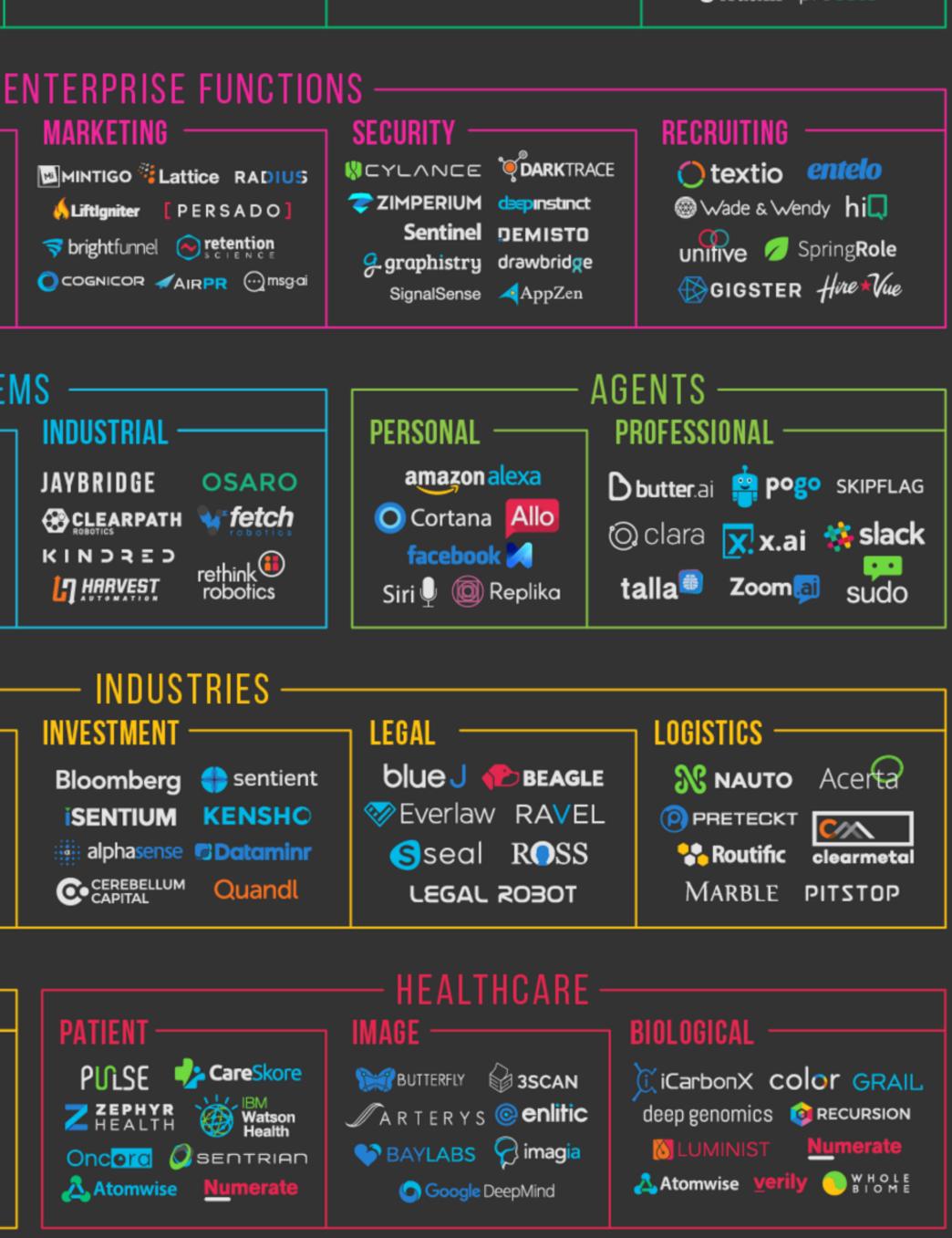


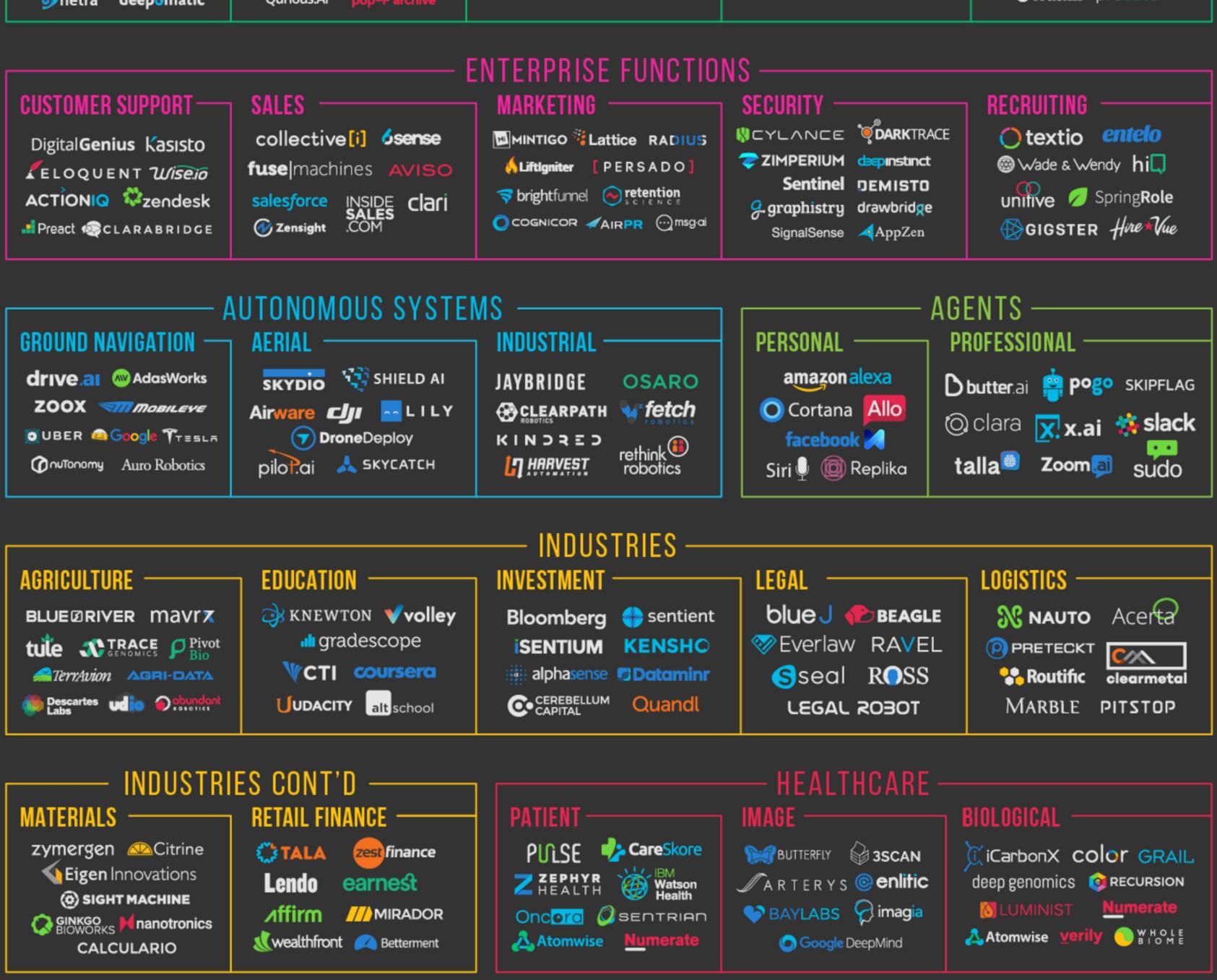


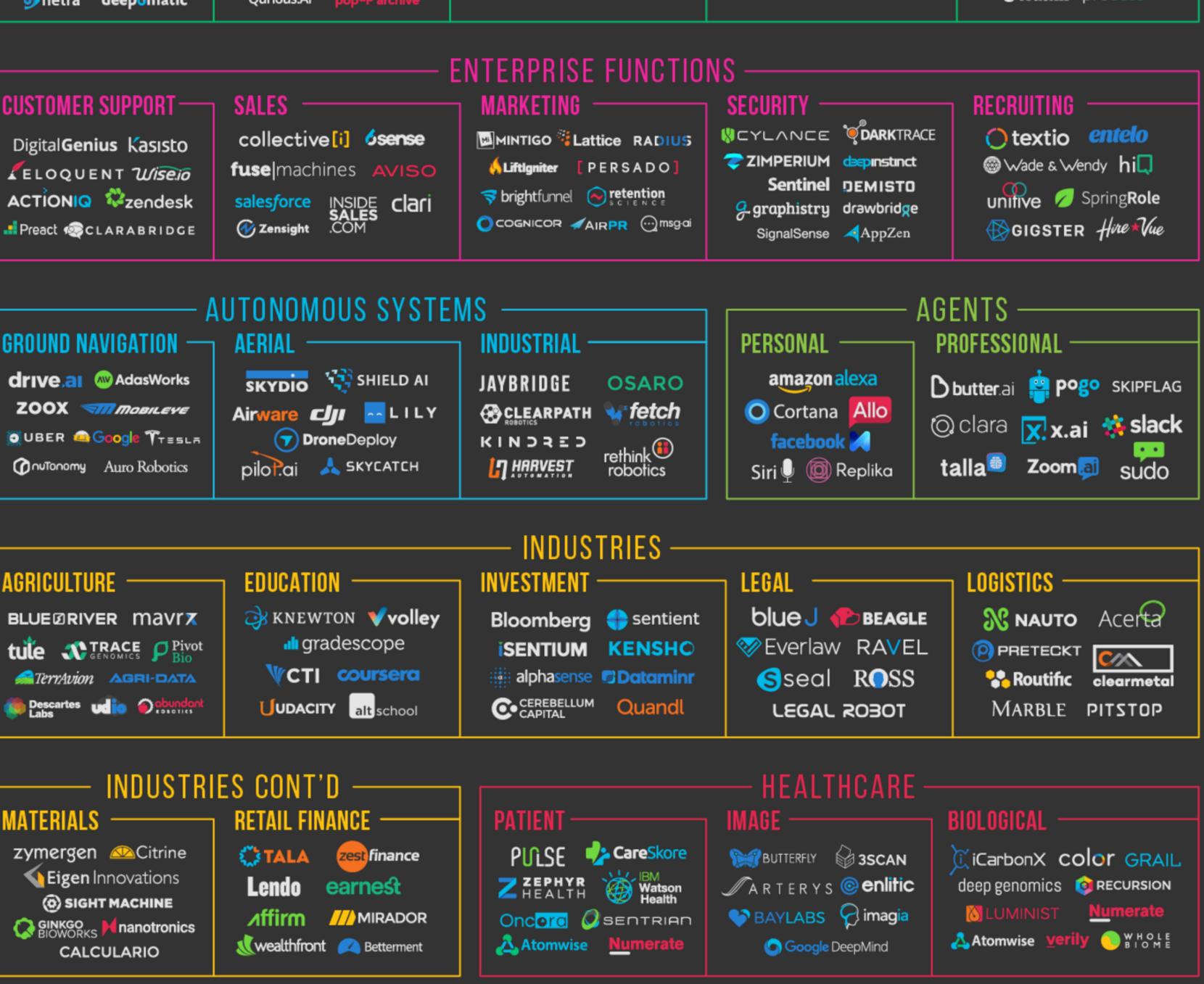
#### TECHNOLOGY STACK — AGENT ENABLERS -OCTANE.AI howdy. Maluub A 🔆 KITTAI OpenAl Gym Kasisto OUTOMOT **N** semantic machines SPARKBEYOND 🧶 rapidminer kaggle DataRobot ŷhat AYASDI **ata iku seldon big MACHINE LEARNING** CognitiveScale 🐵 GoogleML ∝ context relevant Scorp HyperScience Naralogics minds.ai H2O.ai SCALED SCALED SPORKCOGNITION C GEOMETRIC deepsense.io reactive skymind 🥙 bonsai NATURAL LANGUAGE O agolo ♥ FIYLIET LEXALYTICS ( spaCy ( LUMINOSO Narrative Science 📀 cortical.io 🛛 🎯 MonkeyLearn **SIGOPT HyperOpt** fuzzy<sup>io</sup> okite rainforest Ølobe Anodot Signifai LAYER 6 M Sonsai CrowdFlower & diffbot CrowdAl import Paxata **DATASIFT** amazon mechanical turk enigma WorkFusion DATALOGUE OTRIFACTA Parsehub **OPEN SOURCE LIBRARIES** <sup>-</sup> Keras Chainer CNTK **TensorFlow** Caffe H20 DEEPLEARNING4J theano Ttorch

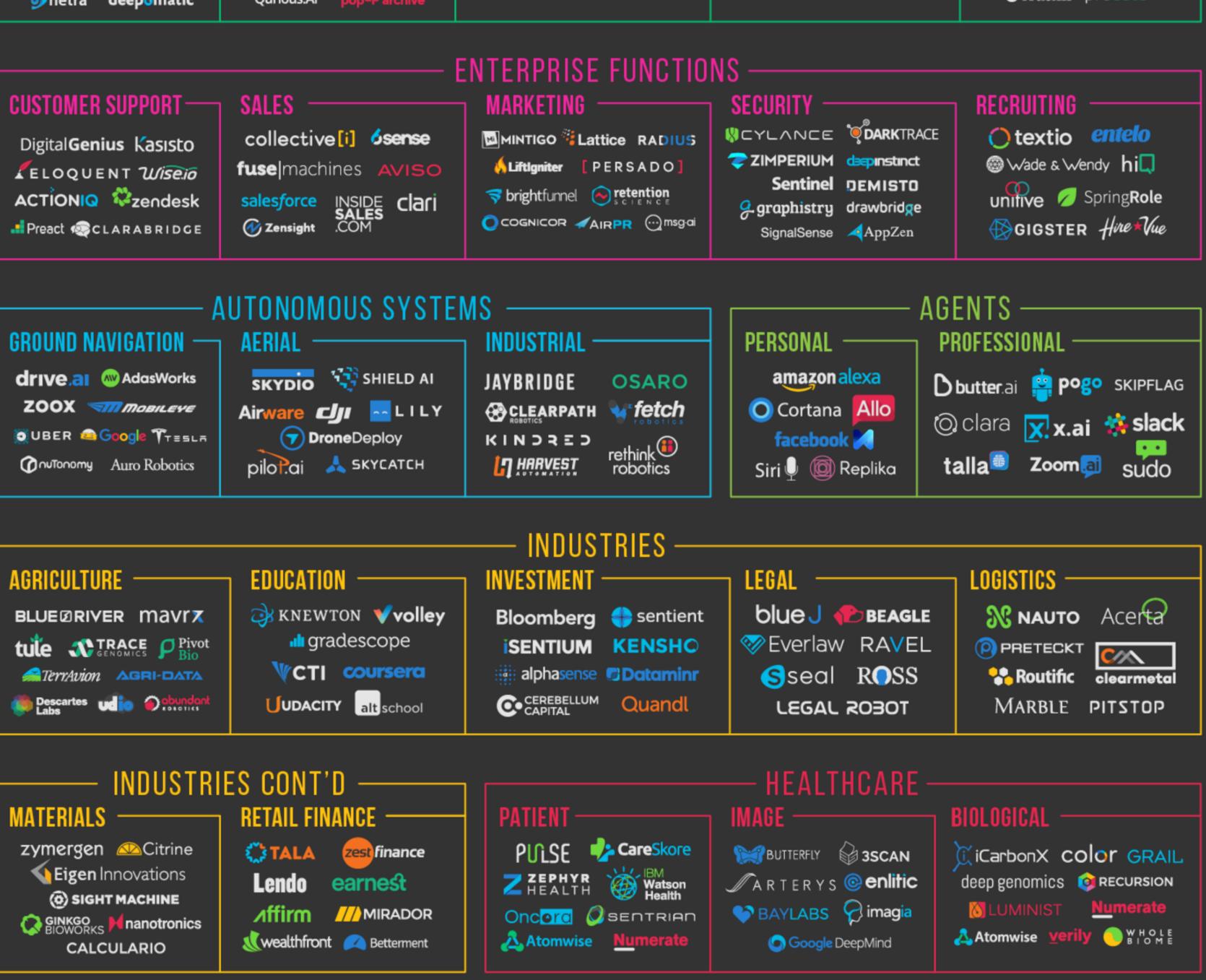


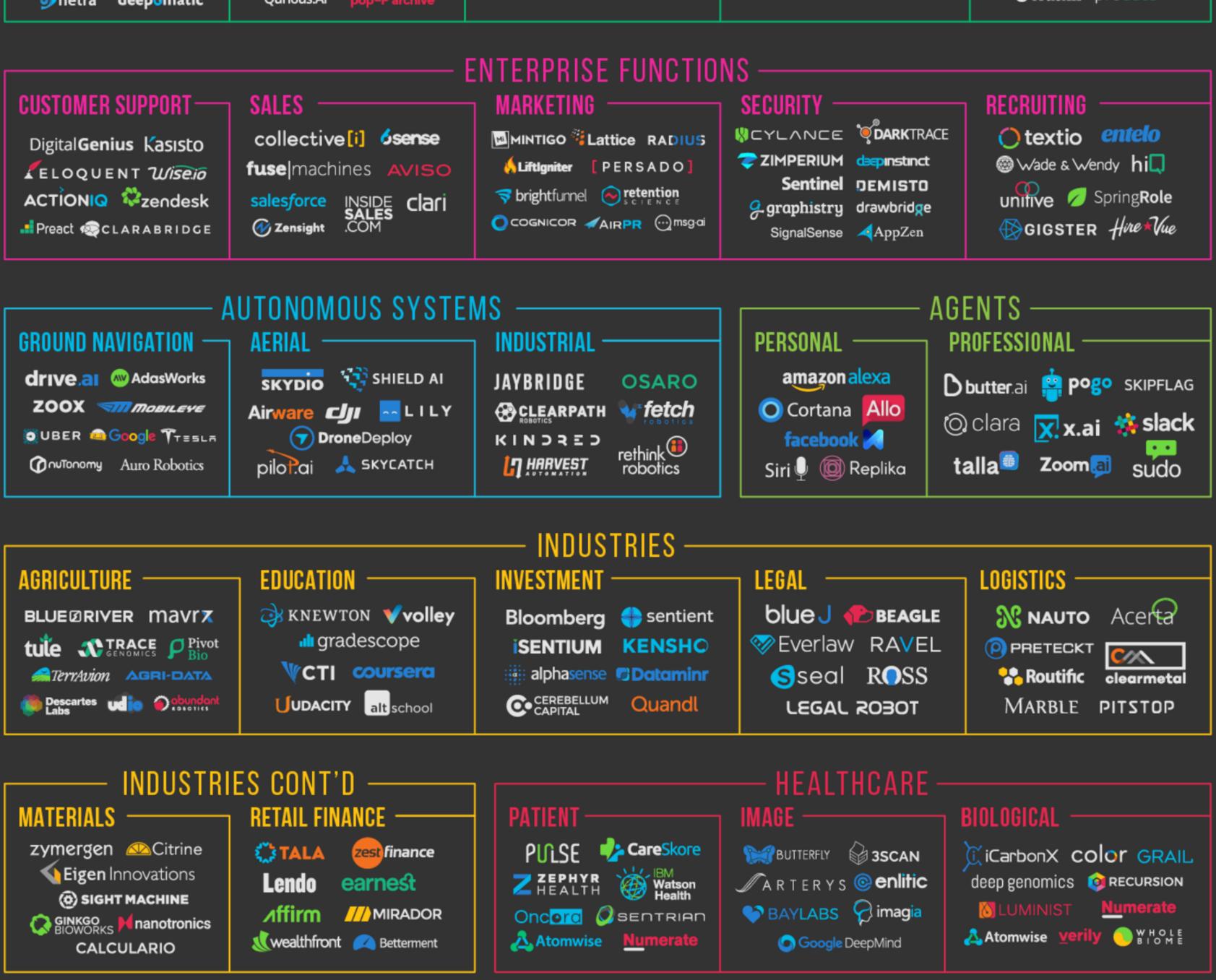
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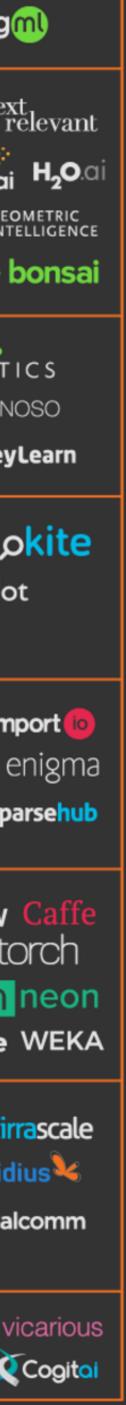




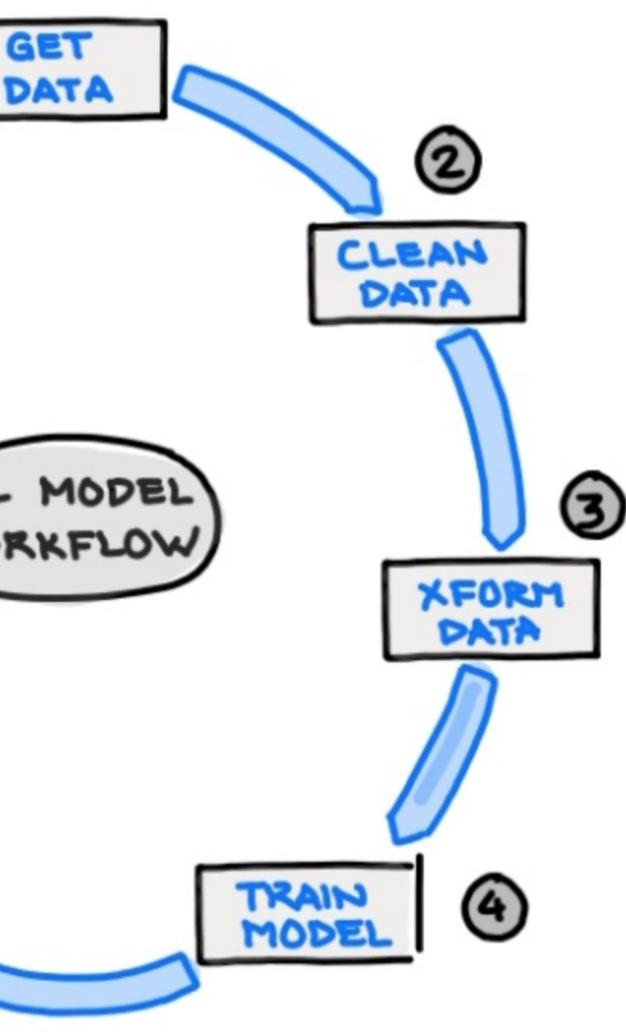


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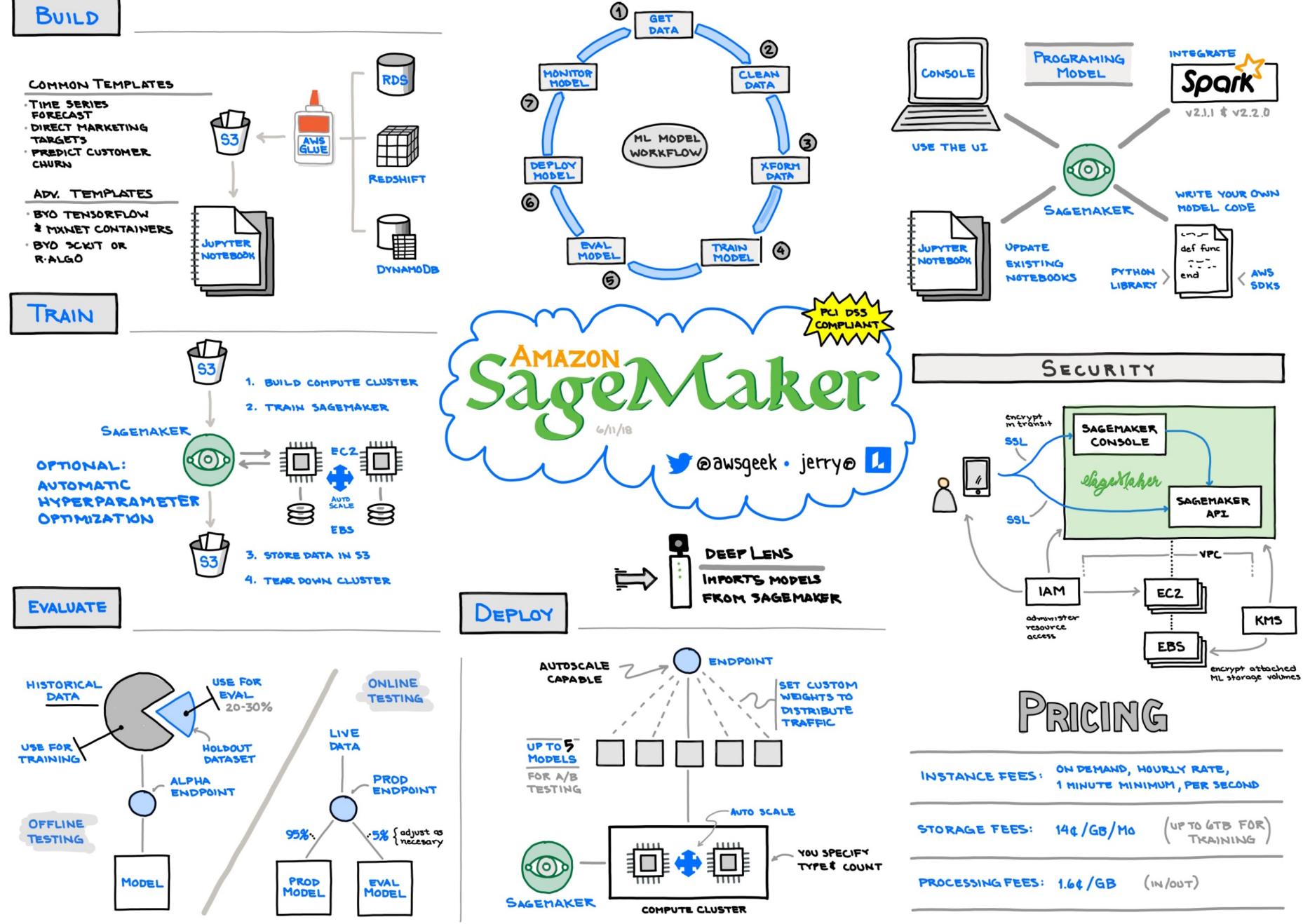


#### Stages of Machine-Learning study in industry (1 GET DATA 2 MONITON CLEAN MODE DATA Ø ML MODEL 3 WORKFLOW DEPLOY XFORM MODE DATA 6 EVAL TRAIN (4)MODEL MODEL 6





#### BUILD



http://bit.ly/2JAaa5h



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lution	$\sim$ t	$\mathbf{N}$	ΝЛΙ	
lution		X		

	ROOT Files	Data Layer	ROOT Files
	Ad hoc ROOT ETL logic	Loading Layer	Numpy / HDF5 Conv Loaders
	TMVA	Training Layer	Keras, TensorFlo PyTorch, XGBoo scikit-learn,
	Deployment Target (TMVA)	Serving Layer	Deployment Tar (lwtnn, TensorFlo TMVA wrapper
. 1 .	HEP (Circa 2013)		HEP (Circa 20 11

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# Engineering

DB / HDFS etc.

onverters /

Numpy / HDF5 Converters / Loaders

rFlow, Boost,

. . .

Keras, TensorFlow, PyTorch, XGBoost, scikit-learn, ...

Target rFlow, oers)

2018)

Deployment Target (TensorFlow Serving, SageMaker, etc.)

Industry



## Notable ML-infrastructure trends

### Automation

- Reuse, reproducibility
- Workflows (Amazon SageMaker)
- Access to data and computing resources
- Continious offline testing

**Development & production integration** ML as a service

- Algorithm design, optimization (studio.ml, modelgym)
- Deployment

#### Interoperability

Open Neural Network Exchange, https://onnx.ai/



# One more trend

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### REINVENTING DISCOVERY

#### The New Era of Networked Science

#### MICHAEL NIELSEN





## Collaboration with Data Science (DS)

Domain science researches do not necessarily have required skills and background to properly adapt those methods (High Energy Physics, Astro Physics, Neuroscience)

Industry or Academic data scientists are eager to help, but sometimes it is difficult for them to cope with domain specificity

junior ML researcher senior ML researcher





### DataScience competition: Netflix Prize

Netflix prize – prediction of DVD titles renting (1M USD)

- training data set of 100,480,507 ratings that 480,189 users gave to 17,770 movies >
- Each training rating is a quadruplet of the form <user, movie, date of grade, grade> >
- The user and movie fields are integer IDs, while grades are from 1 to 5 (integral) stars >
- The qualifying data set contains over 2,817,131 triplets of the form <user, movie, date of grade>, with grades known only to the jury
- A participating team's algorithm must predict grades on the entire qualifying set, but they are only informed of the score for half of the data, the quiz set of 1,408,342 ratings. The other half is the **test** set of 1,408,789, used to find winners.
- Submitted predictions are scored against the true grades in terms of > root mean squared error (RMSE), and the goal is to reduce this error

https://wiki2.org/en/Netflix Prize





### Netflix Prize timeline

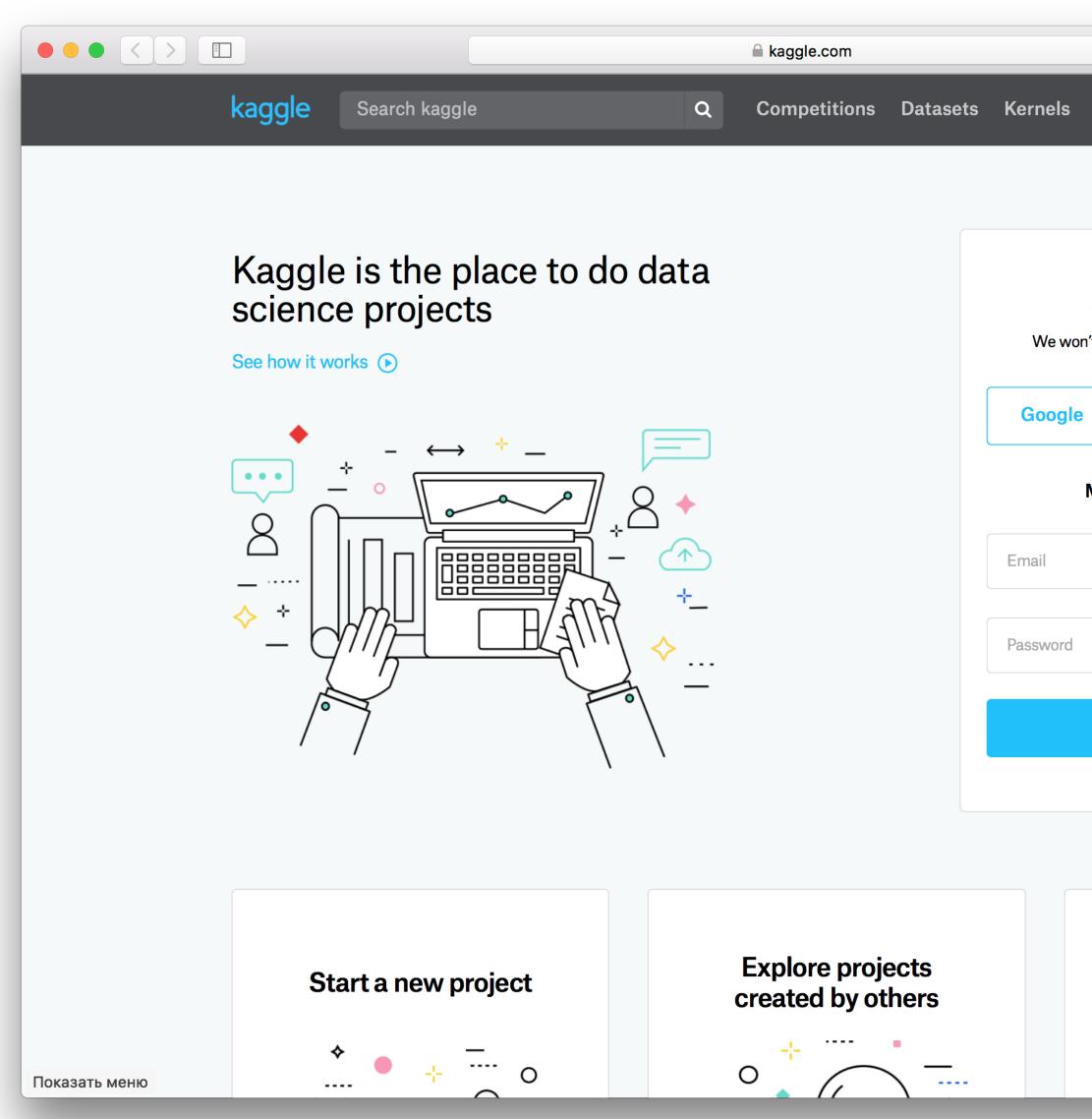
- Netflix prize prediction of DVD titles renting (1M USD for improving baseline by 10%) Baseline algorithm – Cinematch (linear model) >
- Aug 2007 international conference, announcement >
- Oct 2007 BellKor FTW 8.43% improvement! (among 20k teams) >
- Oct 2008 Big Chaos took lead >
- Late Oct 2008 BellKor + Big Chaos 9.43% impovement >
- June 2009 BellKor's Pragmatic Chaos 10.05% >
- 26 July 2009 18:18:28 BellKor's Pragmatic Chaos 10.09% >
- 26 July 2009 18:38:22 Ensemble 10.10% >

Got same result on final test! The prize was awarded to BellKor's Pragmatic Chaos. Second challenge was cancelled due to privacy concerns.

- https://wiki2.org/en/Netflix\_Prize







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<b>F</b> acebook	Vahaa	
Facebook	Yahoo	
Manually create an accou	ınt:	
Sign Up		
Join one of competitie		
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#### O(100) datasets O(1000) competitions O(10000) users O(10<sup>8</sup>) submissions

http://bit.ly/2JDMo8j





## **Competitions on Particle Physics at Kaggle**

Higgs Boson Search > "Discovery" of Xgboost algorith

Flavour of Physics ( $\tau \rightarrow 3\mu$ )

Data doping – nice approach for training on mixture of MC & data

### TrackML

> ... in progress until end of October (co-hosted by Codalab)

Private challenges (YSDA):

> Tracking, PID, EM-showers, for MLHEP schools and local courses

#### **Restrictions:**

Single metric, difficult to check solutions



### Caveats

#### Domain-specific barriers

- Developed terminology and mindset
- Structured and semantically-rich data
- Weird constraints ("systematics", "calibration") due to the fact that ML part is just a step of a bigger picture
- Enormous data flows
- No obvious metrics for 'sanity' checks (is a jet/shower generated by NN looks realistic enough?)

Reproducibility/traceability of results

Peer review?

Motivation for DS people?



### **Research Coopetition**<sup>\*</sup> **Platform Candidates**

Github (belongs to Microsoft)

> No reward mechanism, too generic

Kaggle (belongs to Google)

No micro-reward motivation, no reward for popular contribution, single metric from pre-defined list

### CodaLab

reuse / peer review

Coopetition or co-opetition (sometimes spelled "coopertition" or "co-opertition") is a neologism coined to describe cooperative competition.

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No micro-reward motivation, single metric, no means of publishing /



### **Research Coopetition Platform Features**

### Target audience

> DS-intensive courses / Universities Built on top of existing services

- GitHub, CodaLab, Jupyter, etc
- Data storage

Support for complex workflows Media for dialogue between domains

(more details in backup section)



### **Research Coopetition Platform Benefits**

Motivation for students:

- Mini-grants to participants for computing access
- Motivation through social dynamics of published code (likes/claps/forks) >
- Mini-grants for participants meeting evaluation criteria >
- Automatic reward system through smart-contract evaluation Motivation for problem owners:
- Many students may eventually improve well-formulated problems Motivation for advanced ML/DS:
- New datasets / settings that they can develop own method for Motivation for universities:
- > Keep student's contribution, more adequate grading



### Personal Experience

### 3 projects in that format during 2018/2019 across several universities: > YSDA, HSE, MIPT, CSC 5 summer student projects in collaboration across > HSE, YSDA, MIT, DCU, MIPT One of the master-student projects has been advanced to the level of mature publication in applied Computer Science



### Conclusion & Focus points

Trends in data processing and analysis:

- algorithms get more and more sophisticated thanks to Machine Learning
- new sub-domains emerge in Data Science >

ML will continue to play an increasingly important role in science. How can we scale and cooperate?

- learn to speak ML-language (reasoning, dictionaries, intuition) >
- adoption of best industrial practices
- cooperation with academic ML teams
- inclusion of PhD curricula of ML courses from ML academic partners
- tools flexibility, reproducibility

Research Coopetition Platform (global, diverse, blockchain)

instrumentation gets more powerful (workflows, virtualization, testing, experiments)

anaderiRu@twitter austyuzhanin@hse.ru Backup





### Successful Citizen-Science project check list

- Clear goals, context and ambitions
- marketing

If you want to eat an elephant do it one bite a time

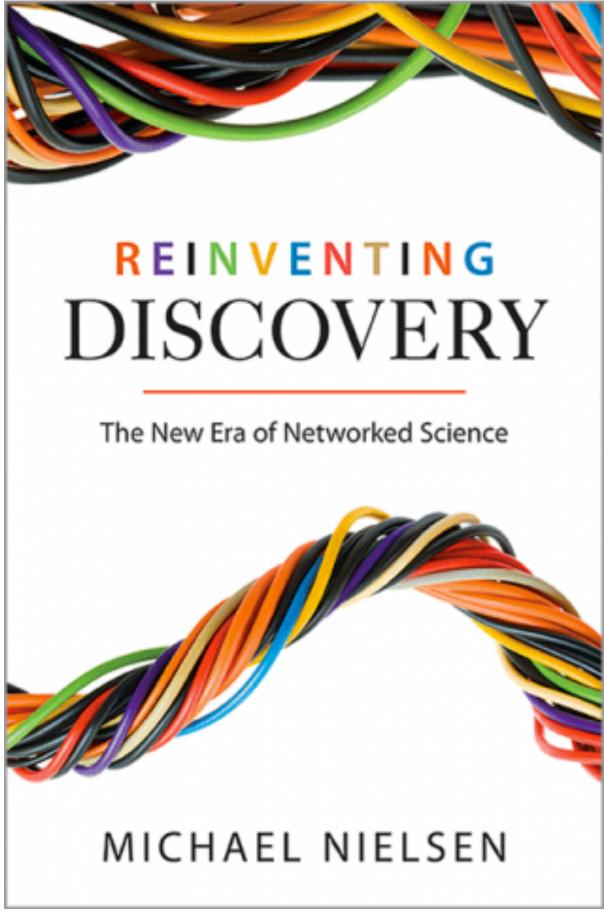
Split big goal in feasible steps

Participant's motivation even for weakly involved ones Specialist attention focus at percise moments

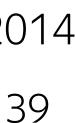
- Progress announcemnts
- Short contribution check cycle Check or reuse artifacts created by other participants Explanatory materials, methodological manifest, convention



# **REINVENTING**



Michael Nielsen, Reinventing the Discovery, 2014



### Target Audience

### There are numerous people passing online ML courses, looking for decent problems to test their skills on

- Low-responsibility contribution >
- Need for computational resources >
- No time/resources for deep problem understanding
- Hungry for scoring records



### High-level platform Components

Reusable artifacts

Problem Directory

Resources (computational, storage)

> Institute / Univsersity

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Problem Owners

Participants, communities



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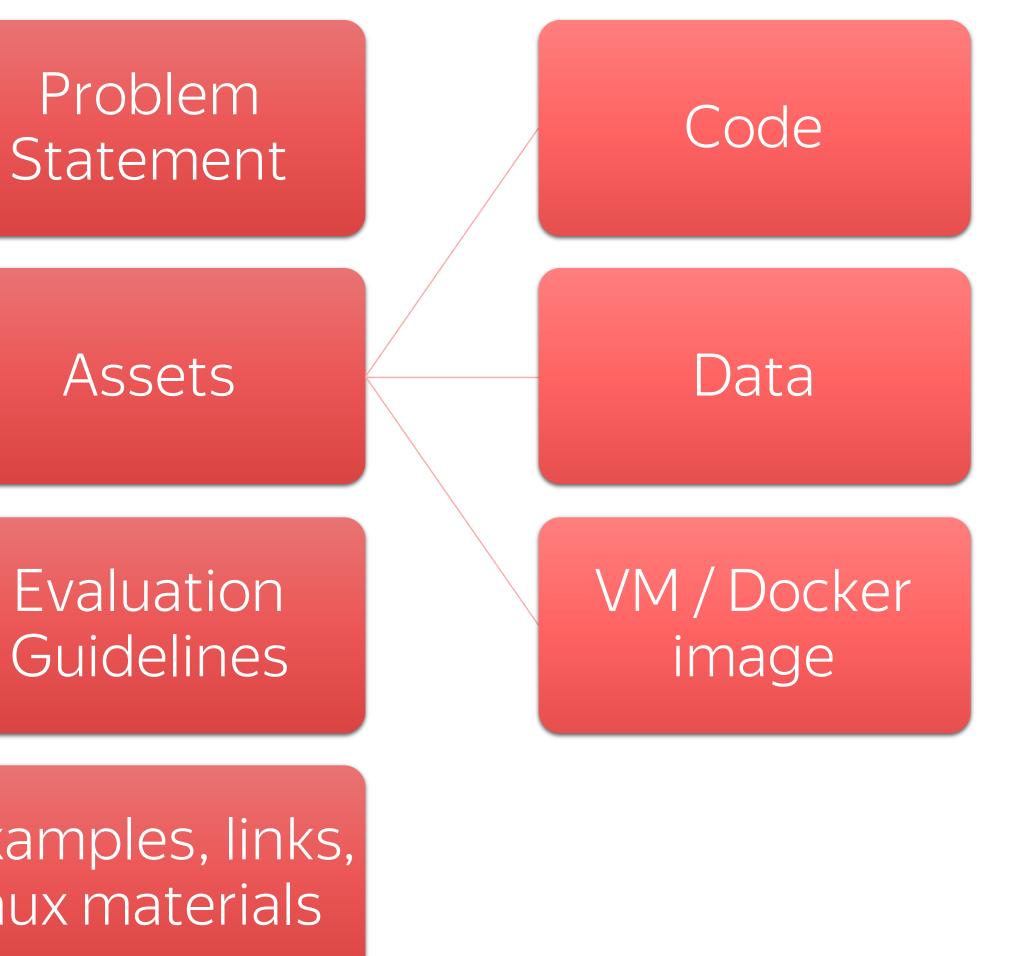


### Problem Structure

#### Problem

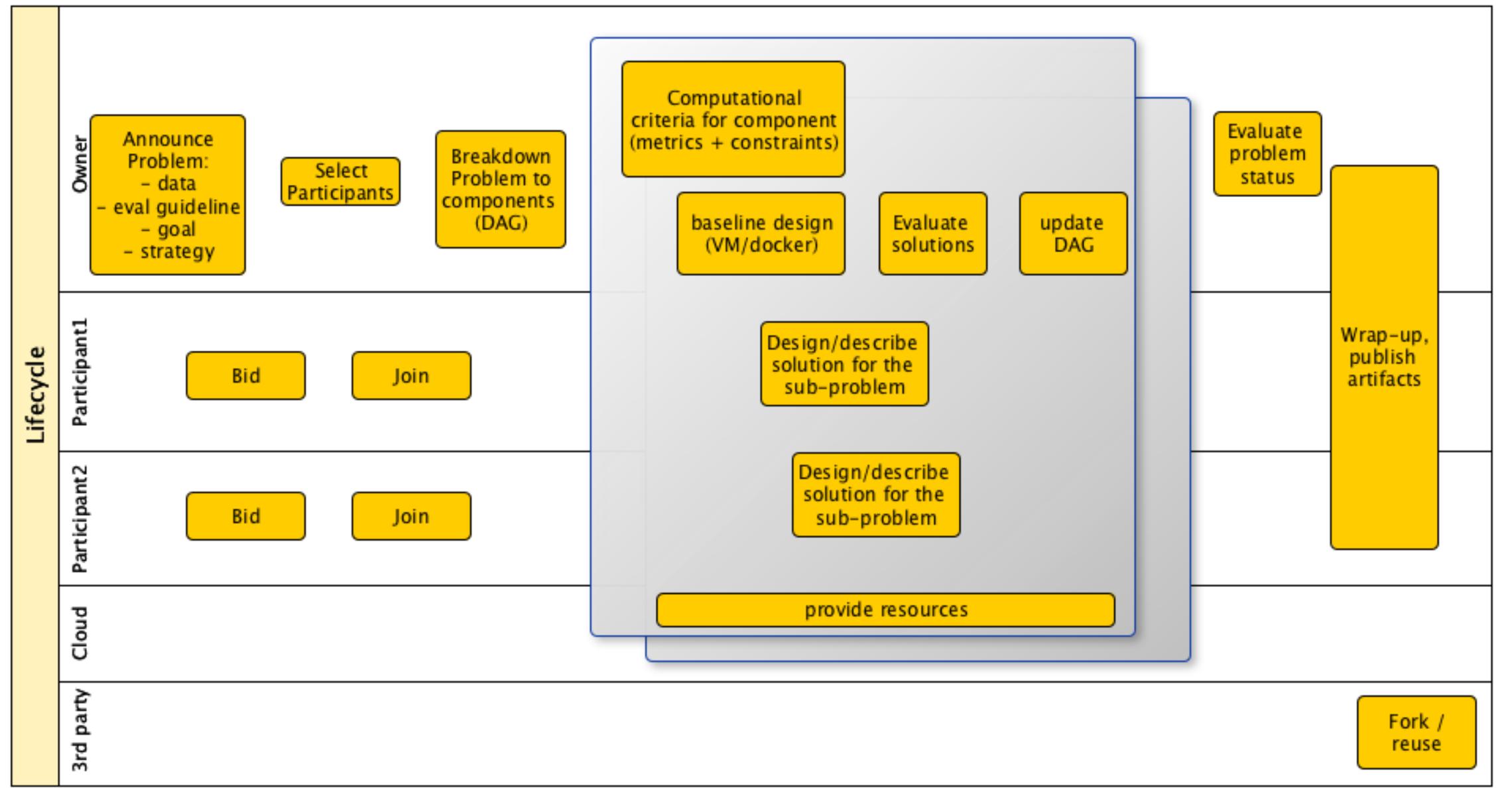
Evaluation Guidelines

Examples, links, aux materials





### **Collaboration Lifecycle**





## **Collaboration Highights**

**Preparation-stage** 

- Define the case goal(s), make it as independed nt as possible Specify reasoning model, make it as clear as possible
- Produce dataset(s), describe the structure >
- Produce evaluation baseline

#### **Research-iterations**

- Describe Figures of Merit (FOM) and constraints clearly Be comfortable with FOM evolution, repeat in cycles (sprints)
- Cycles are time-boxed
- For solution preparation and evaluation external resources are needed

#### Wrap-up stage

- Publish reusable artifacts + result communication Generate track record for *each participant*, estimate impact of each contribution



# What about diversity?

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## Blockchain - A Distributed Ledger Technology

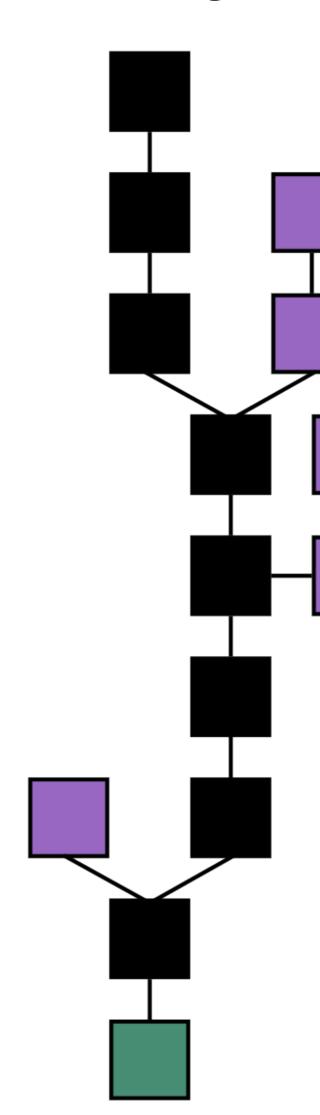
A blockchain is a linked list where each node is connected to its predecessor by a cryptographic hash

All pointing back to the "genesis" block (right, in green) which may contain defining information about the rules for the blockchain protocol

In this way a blockchain comprises a verifiable public ledger Each node of the linked may contain additional transaction data (verifiable) Typically it's the longest contiguous chain (right, in black) which is considered valid (purple are orphaned blocks)

However it's up to the developers who define the protocol to determine the rules for consensus and evolution of the chain

A variety of blockchains exist today, some exploring alternative architectures to test multiple aspects of scalability



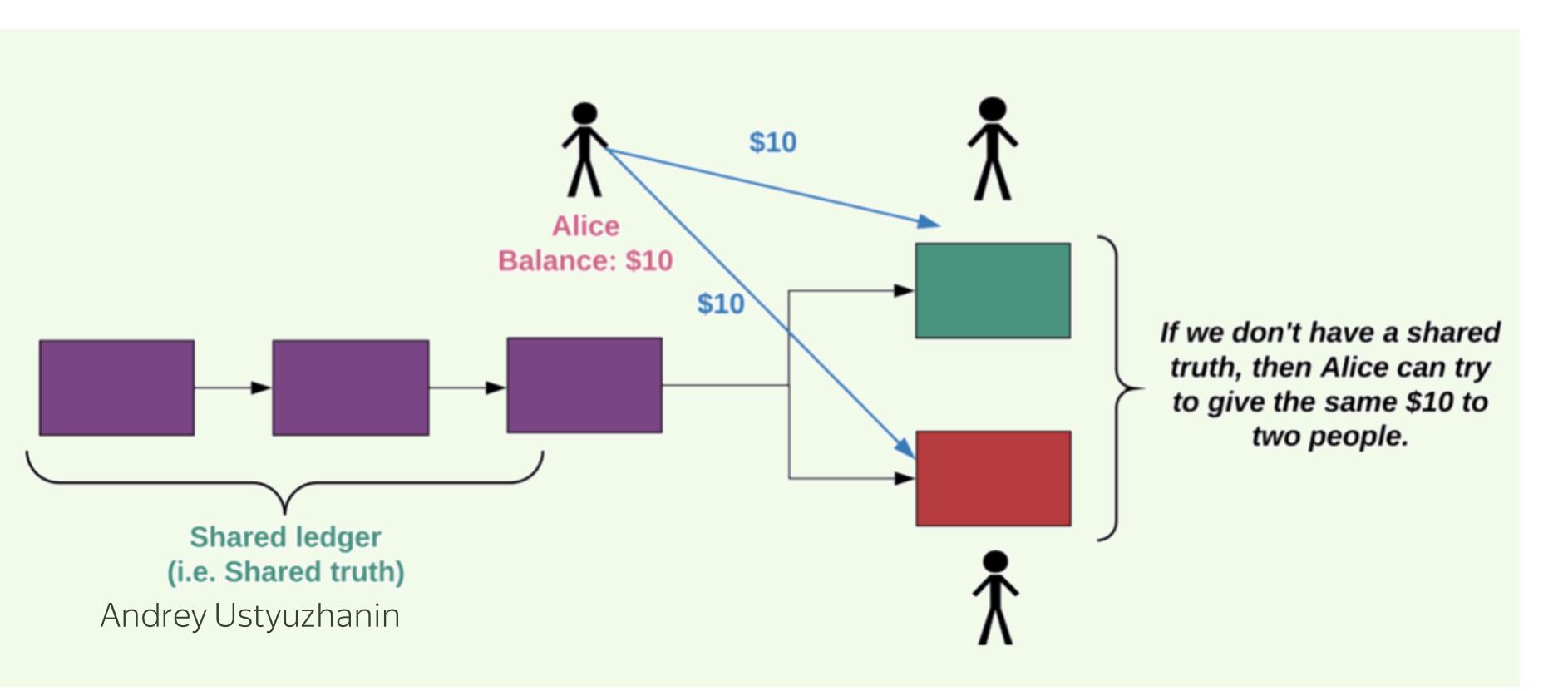


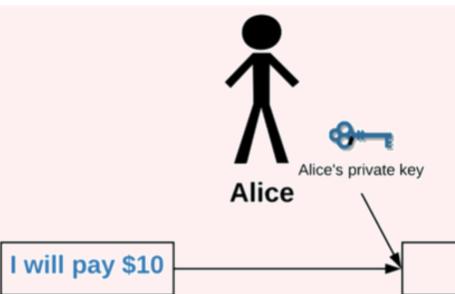


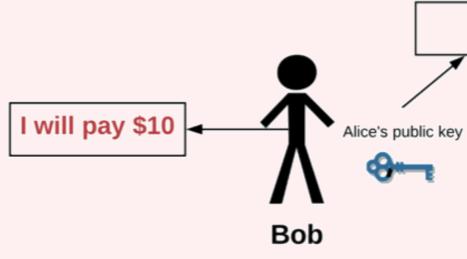
### **Blockchain - A Distributed Ledger Technology**

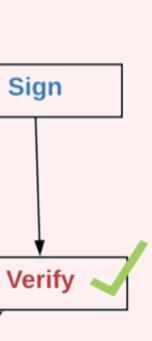
Original purpose of the blockchain:

- Keep shared (consensus) state of the "truth"
- For example balance on each participant's account >











### Blockchain – Smart Contract

Newer blockchains, Ethereum for instance, implement virtual machines that can execute byte code

Smart contracts, implemented in this code allow binding between blockchain addresses and actions that are taken by the code

Typically the same code gets executed by all nodes in the network (extension of Nakamoto consensus) This can be used to implement a huge range of tasks

- sub-currencies
- timed payments
- running of mathematical proofs

Limited by blockchain transaction speed

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```
pragma solidity ^0.4.21;
```

```
contract Coin {
// The keyword "public" makes those variables
// readable from outside.
address public minter;
mapping (address => uint) public balances;
// Events allow light clients to react on
// changes efficiently.
event Sent(address from, address to, uint amount);
// This is the constructor whose code is
// run only when the contract is created.
function Coin() public {
     minter = msg.sender;
function mint(address receiver, uint amount) public {
    if (msg.sender != minter) return;
```

```
balances[receiver] += amount;
```

```
function send(address receiver, uint amount) public {
 if (balances[msg.sender] < amount) return;</pre>
 balances[msg.sender] -= amount;
 balances[receiver] += amount;
 emit Sent(msg.sender, receiver, amount);
```

#### A simple example of a derived currency

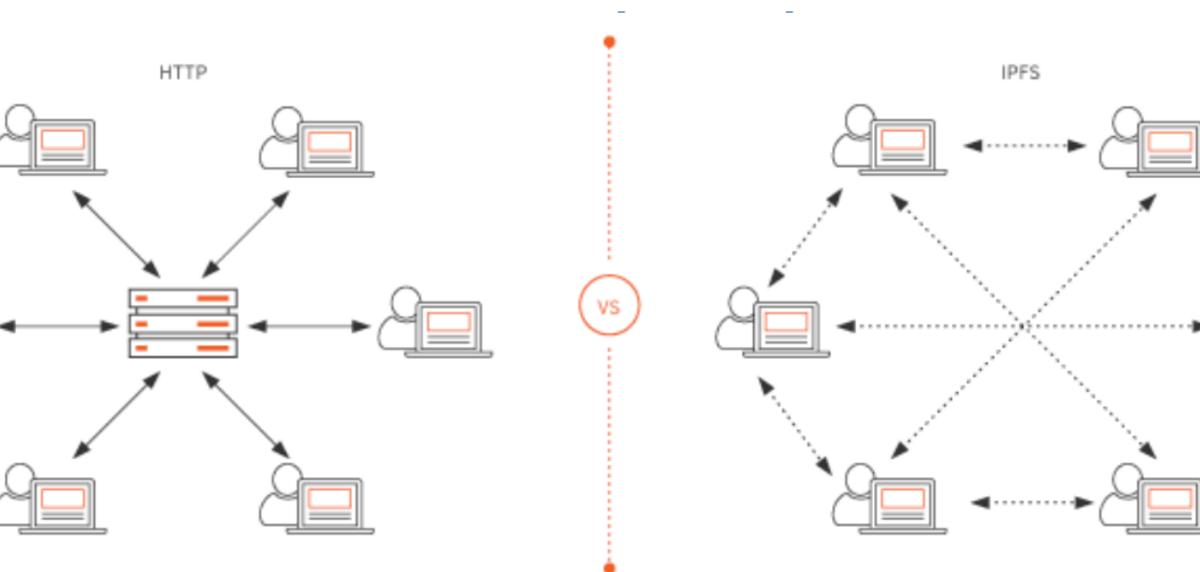




### **Blockchain application**

Based on existing crypto-token Stores artifacts Manages computational resources allocation Records and rewards microcontributions Commit Forks Remove bottle-neck and single

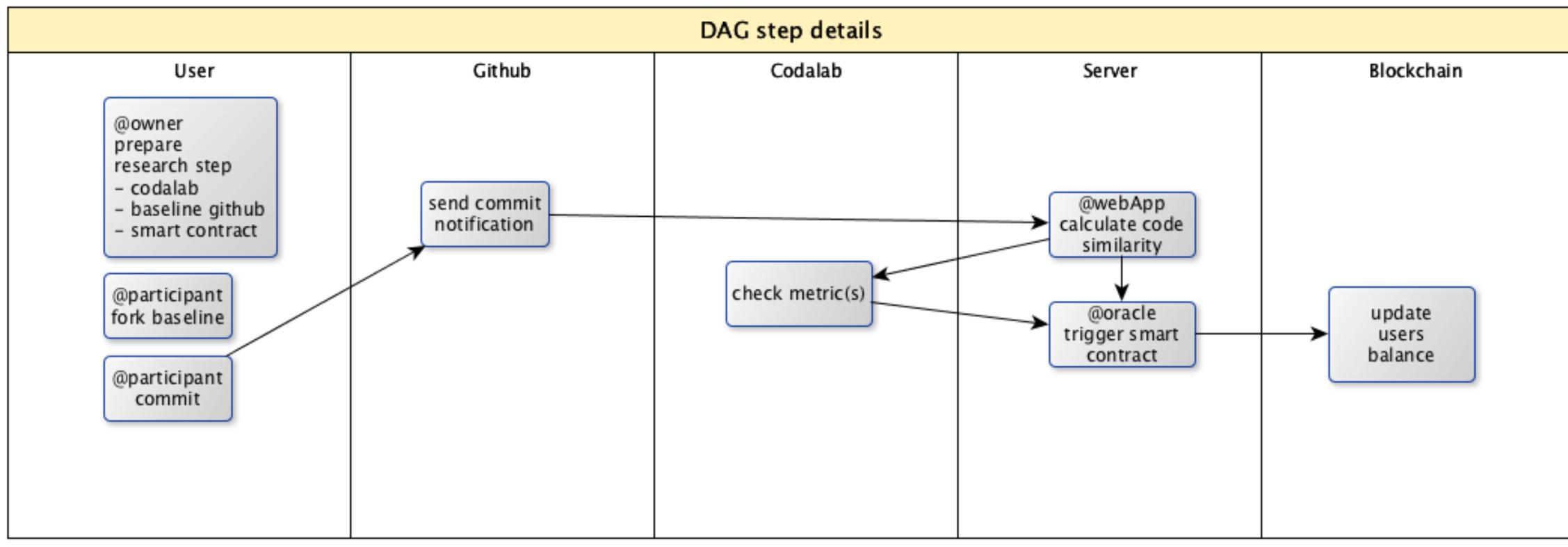
vendor lock







### DAG step (problem component) details





### Blockchain application. Challenges

#### Bootstrapping

- Organizational (institutes / online education systems) >
- Marketing >

Should there be feedback loop from solution running in production?

