Introduction to probabilistic programming languages (PPLs)

Andrés R. Masegosa and Thomas D. Nielsen

Plan for this week

Day 1: Probabilistic programming

- Introduction to probabilistic programming
- Probabilistic programming in Pyro

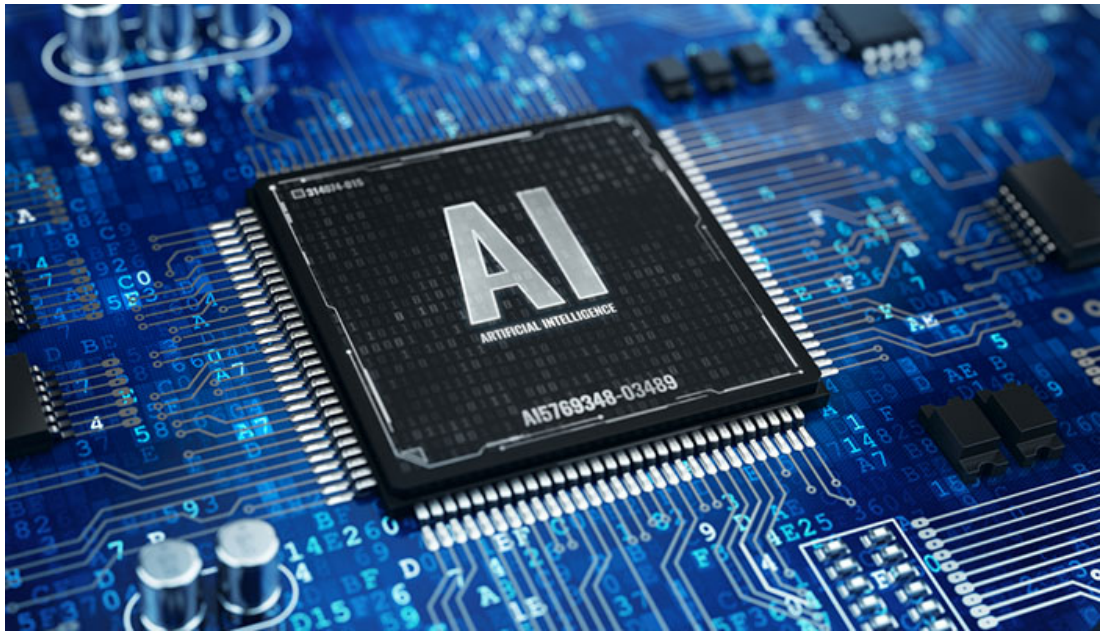
Day 2: Variational inference

- Recap of variational inference (variational inference as optimization)
- Derivation and implementation of selected examples
  - Bayesian linear regression
  - Factor analysis
  - ...

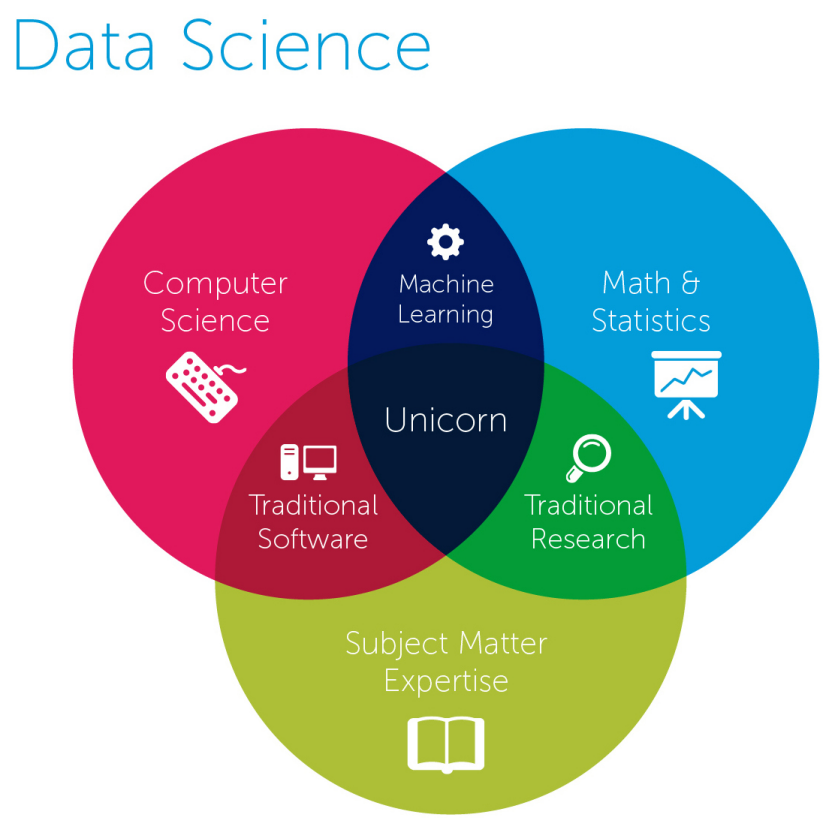
Day 3: Variational inference – cont'd

- Black box variational inference
- Variational inference in Pyro
- Variational auto-encoders

Machine Learning Systems



The development of **machine learning systems** requires enormous efforts.



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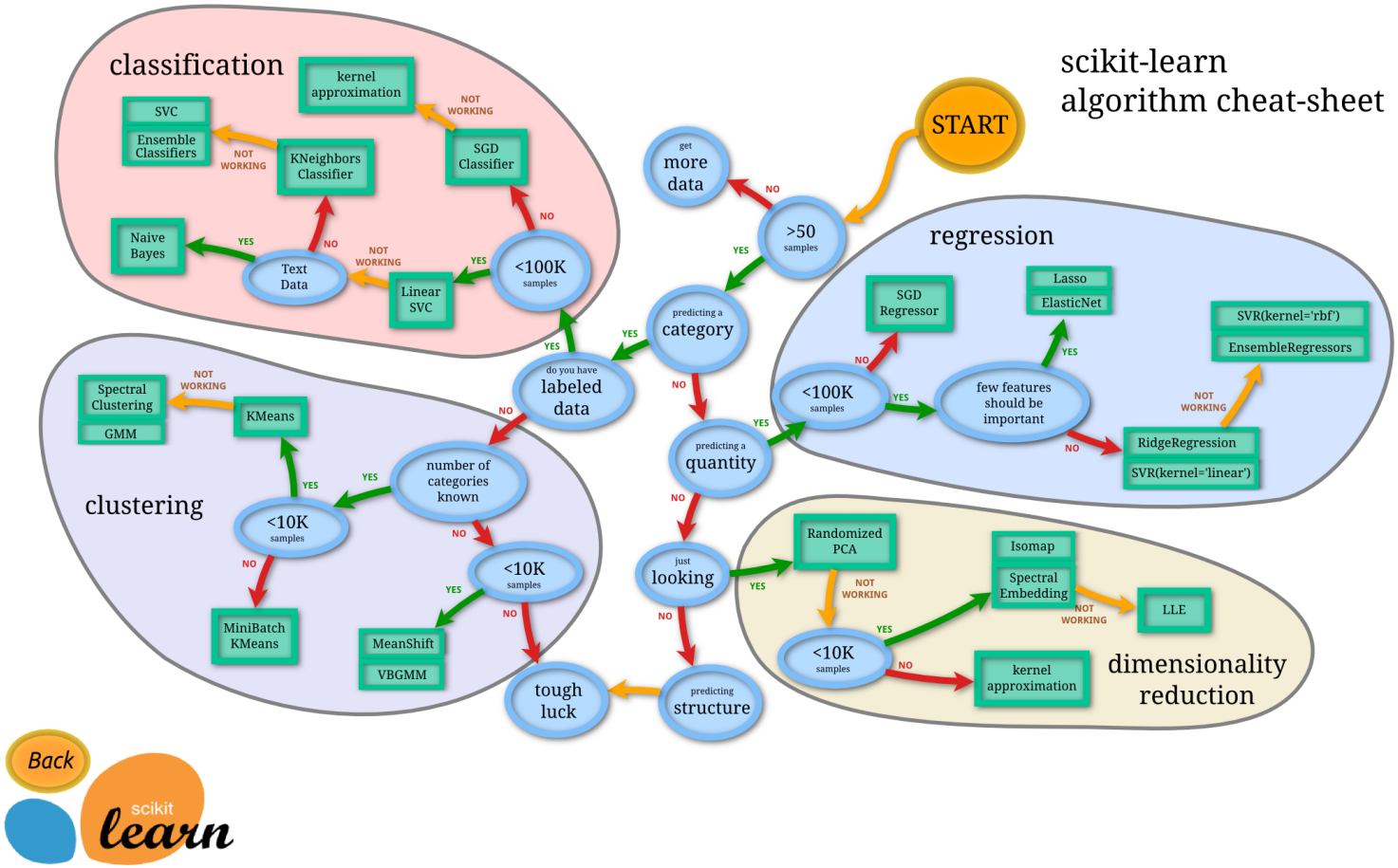
Machine Learning Systems

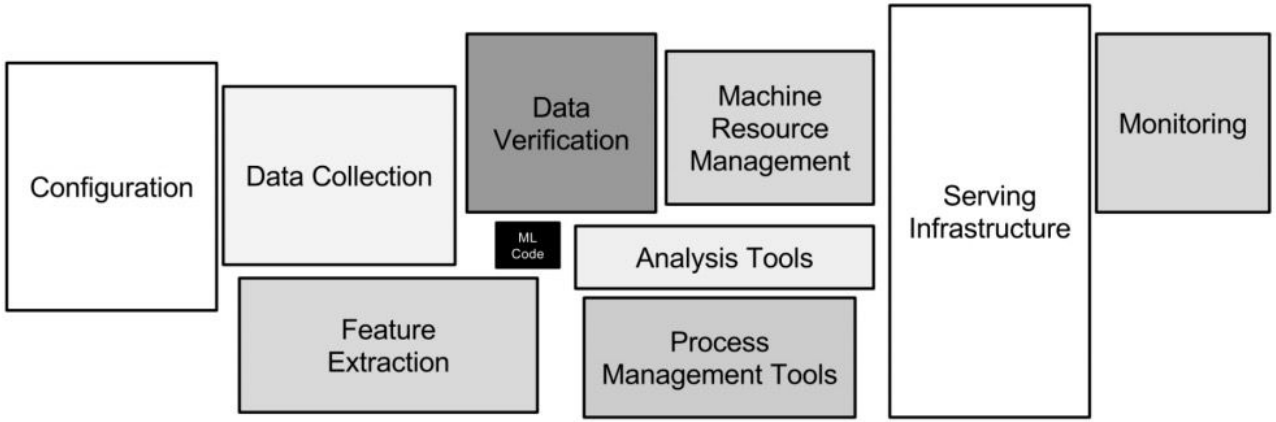


The development of machine learning systems requires enormous effort.

- It is necessary to have highly qualified experts.
- **It is difficult to find the ML model most suitable for an application.**

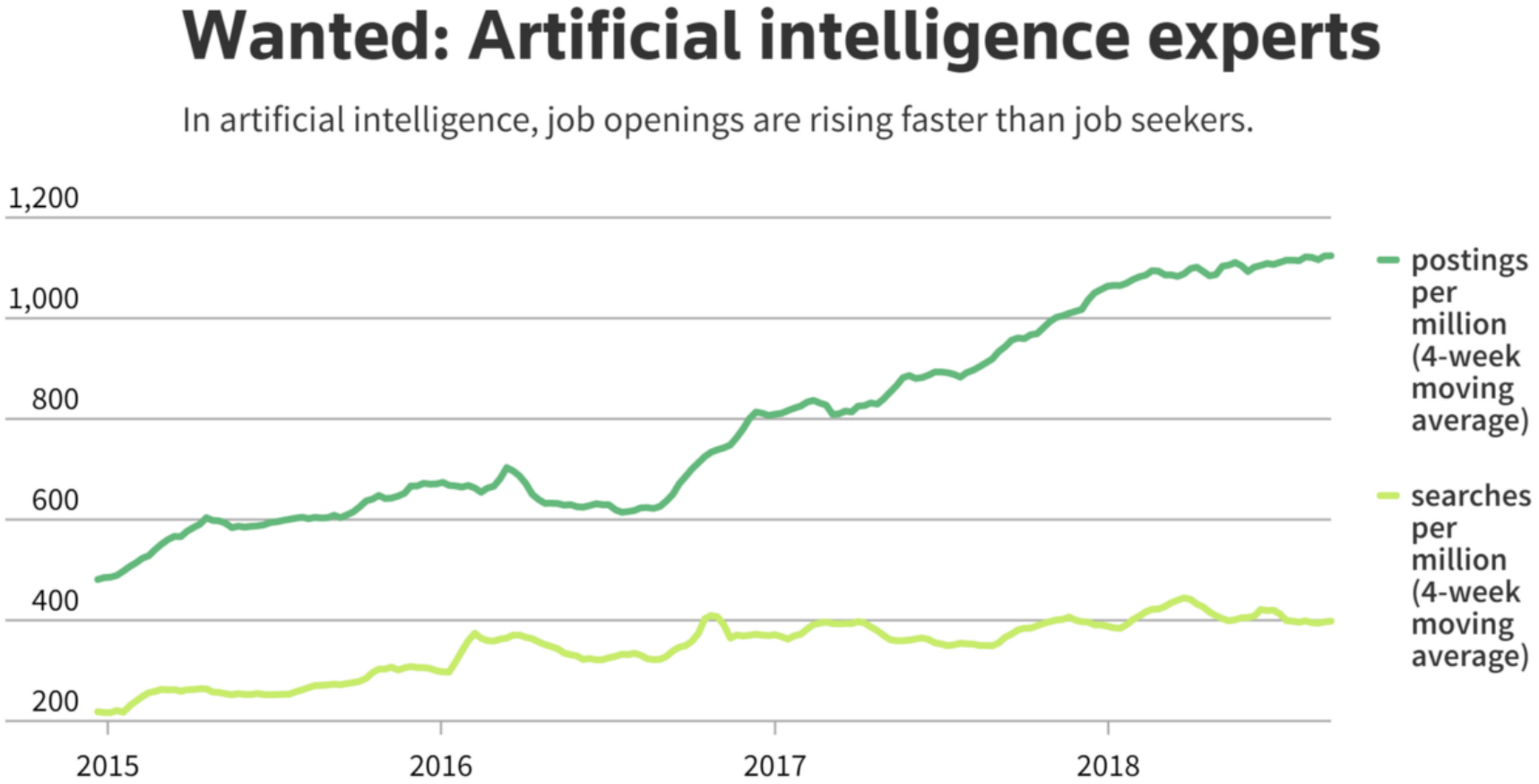
Hidden Technical Debt in Machine Learning Systems

D. Sculley, Gary Holt, Daniel Golovin, Eugene Davydov, Todd Phillips
{dsculley,gholt,dgg,edavydov,toddphillips}@google.com
Google, Inc.



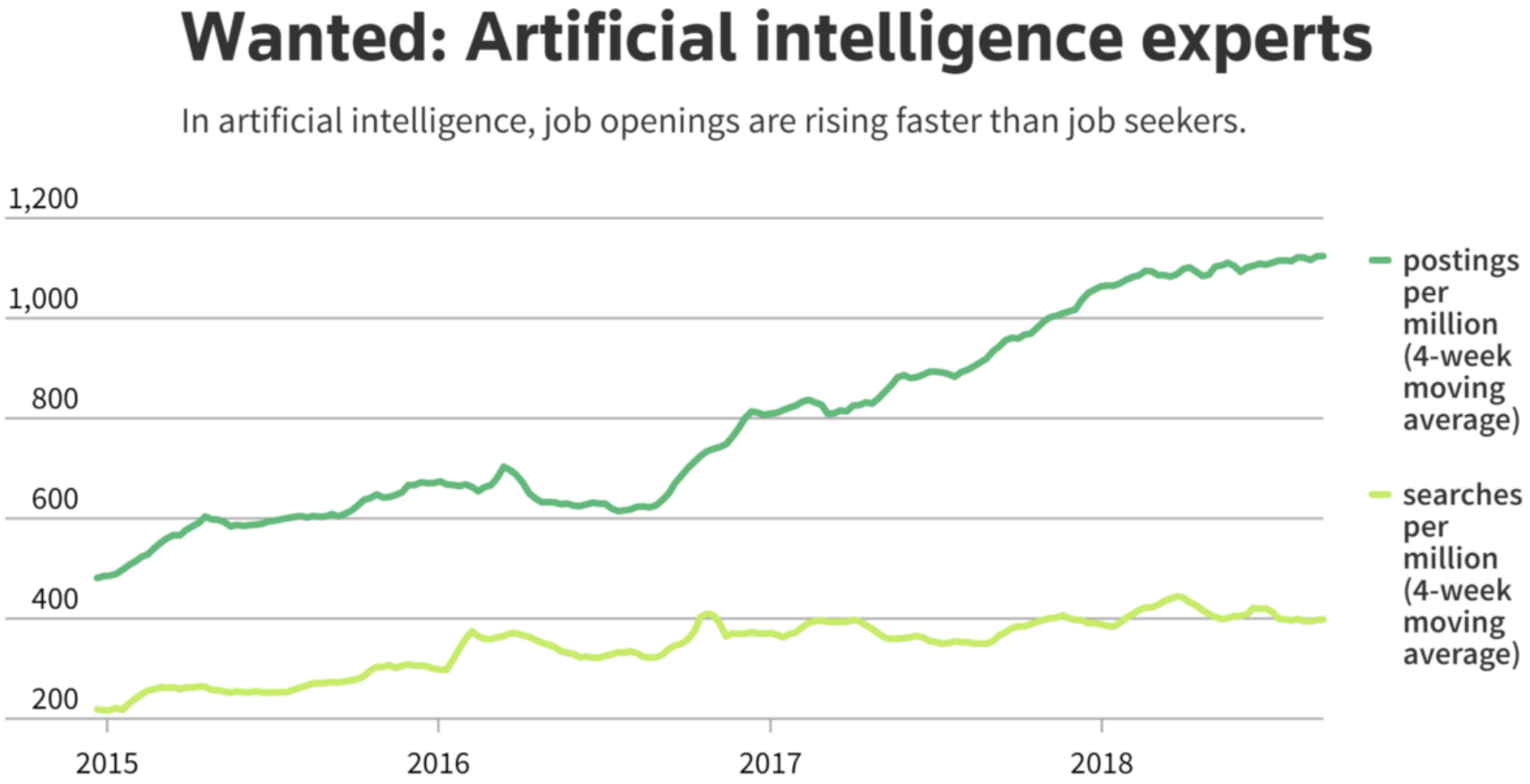
The development of machine learning applications requires enormous effort.

- It is necessary to have highly qualified experts.
- It is difficult to find the ML model most suitable for an application.
- **Programming a ML model is a complex task where many problems are intermingled**.



Consequences:

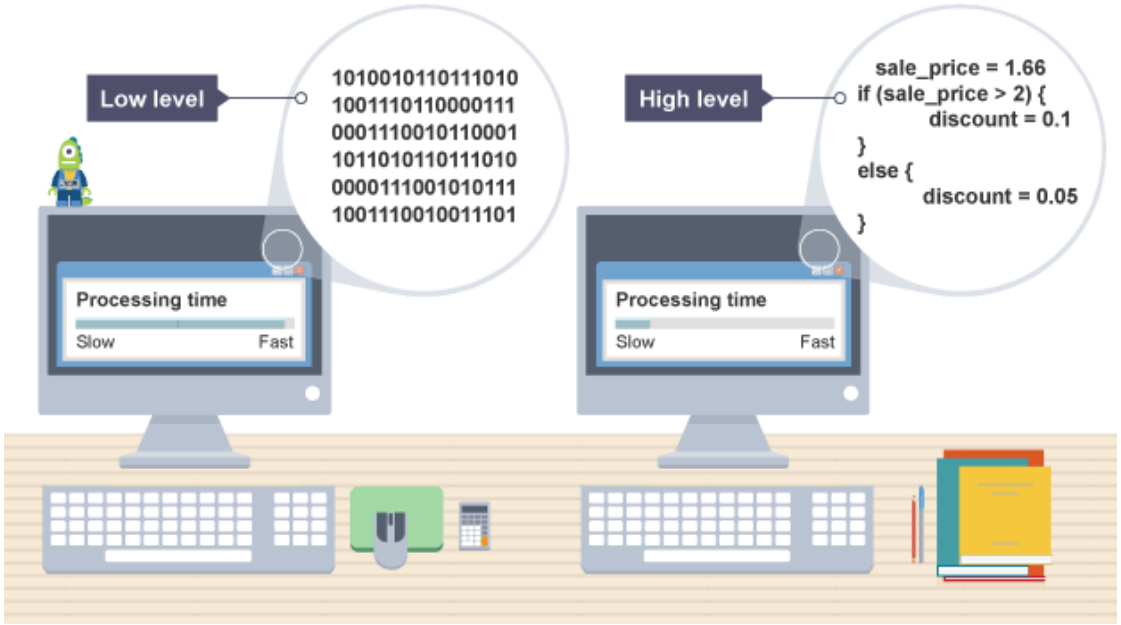
- Shortage of AI experts (and high salaries).



Consequences:

- Shortage of AI experts (and high salaries).
- Only big corporations have the resources for developing ML systems.

Programming Languages



Similar situation than 50 years ago:

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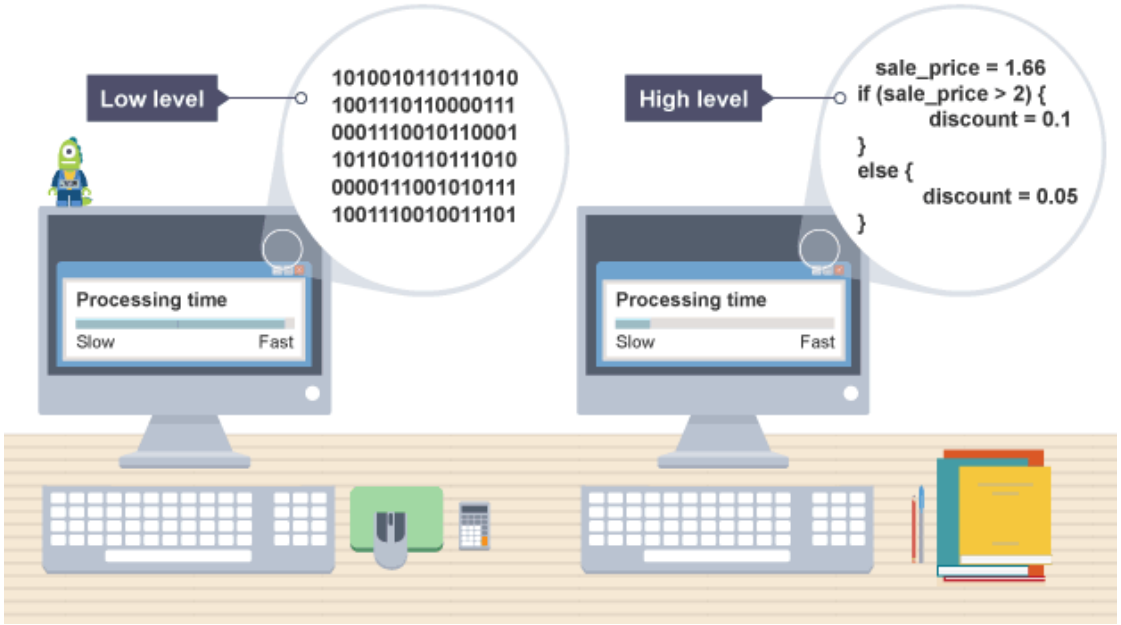

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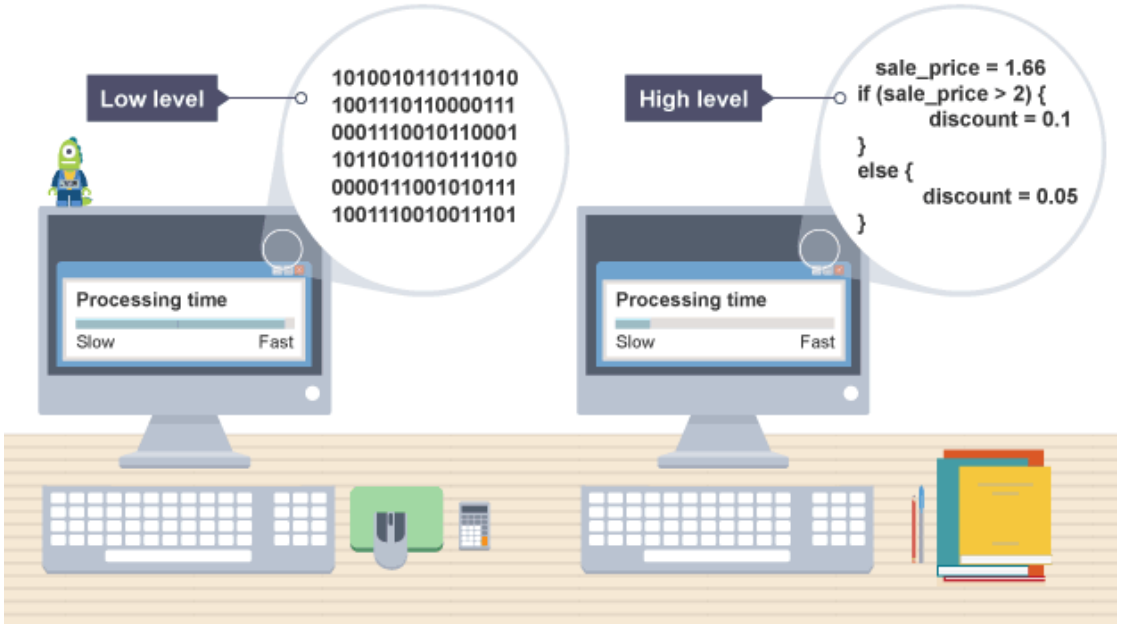

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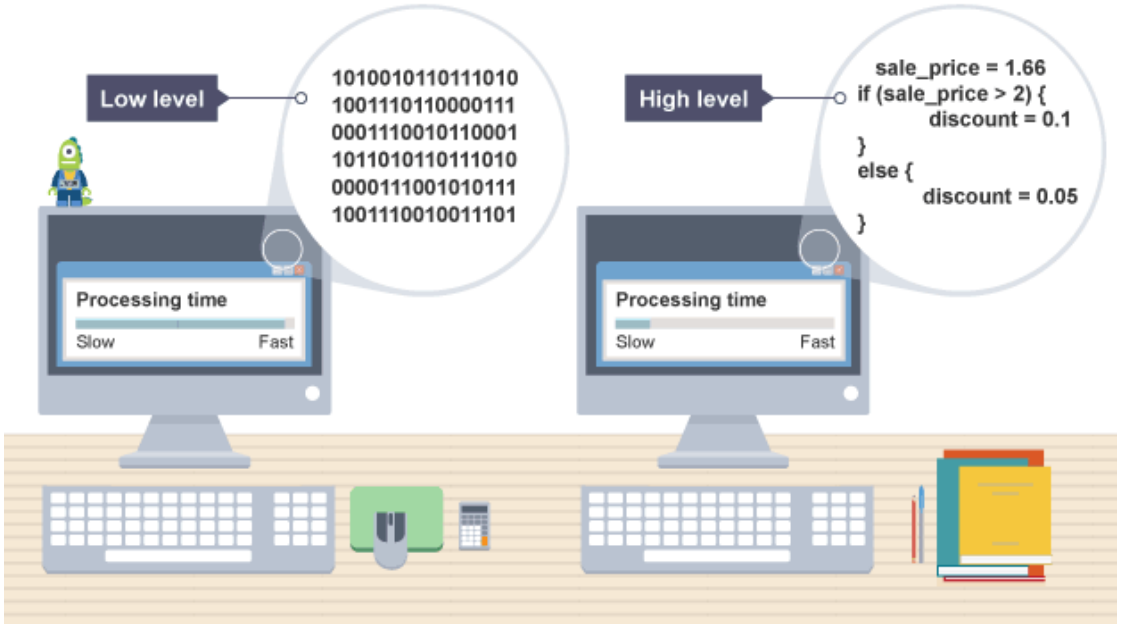

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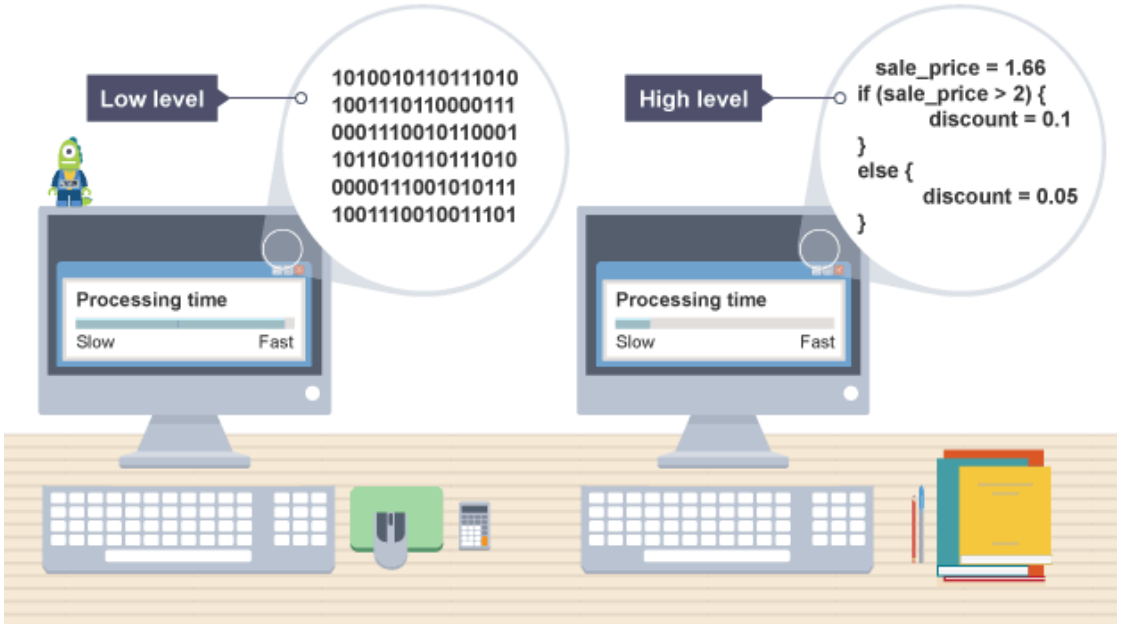
- Programming was complex and demand high-expertise.
- Focus on application and low-level hardware details.

Programming Languages



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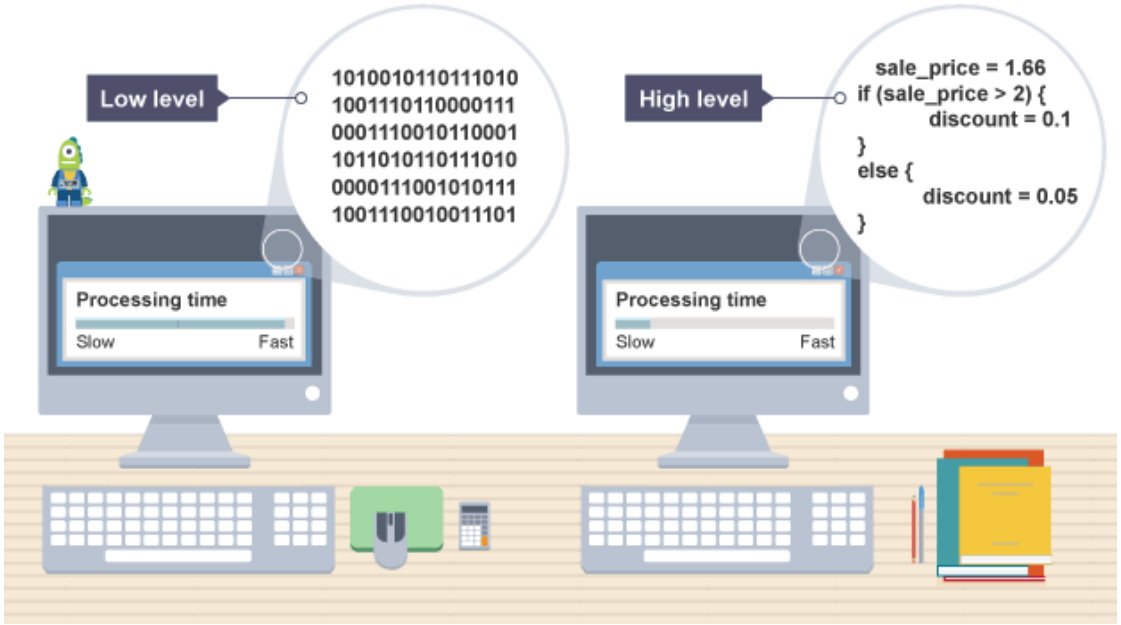

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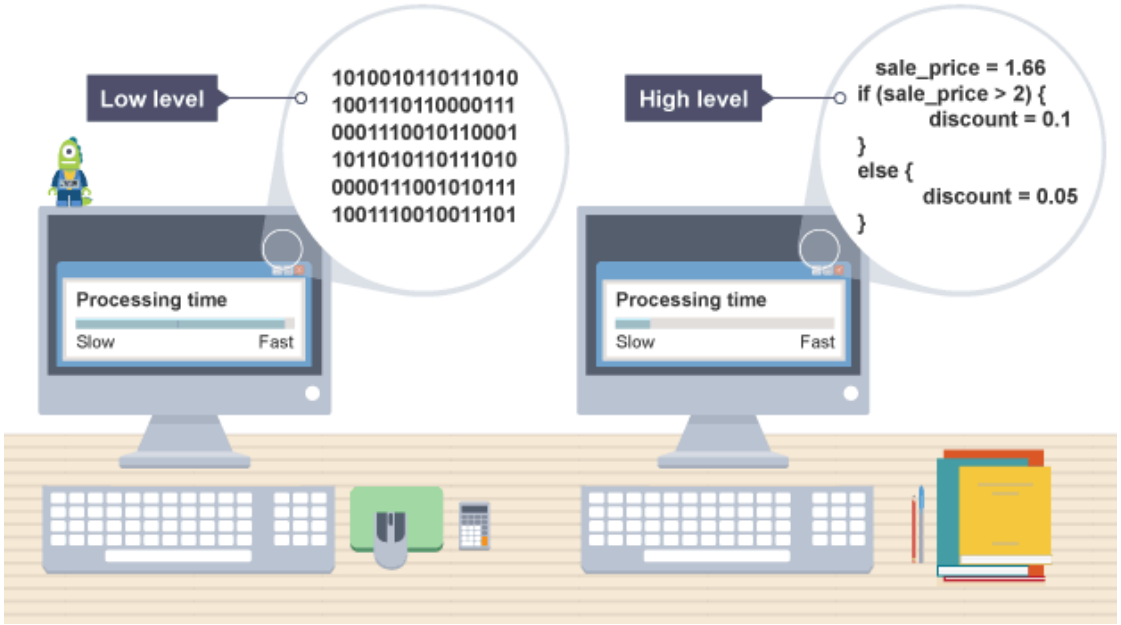

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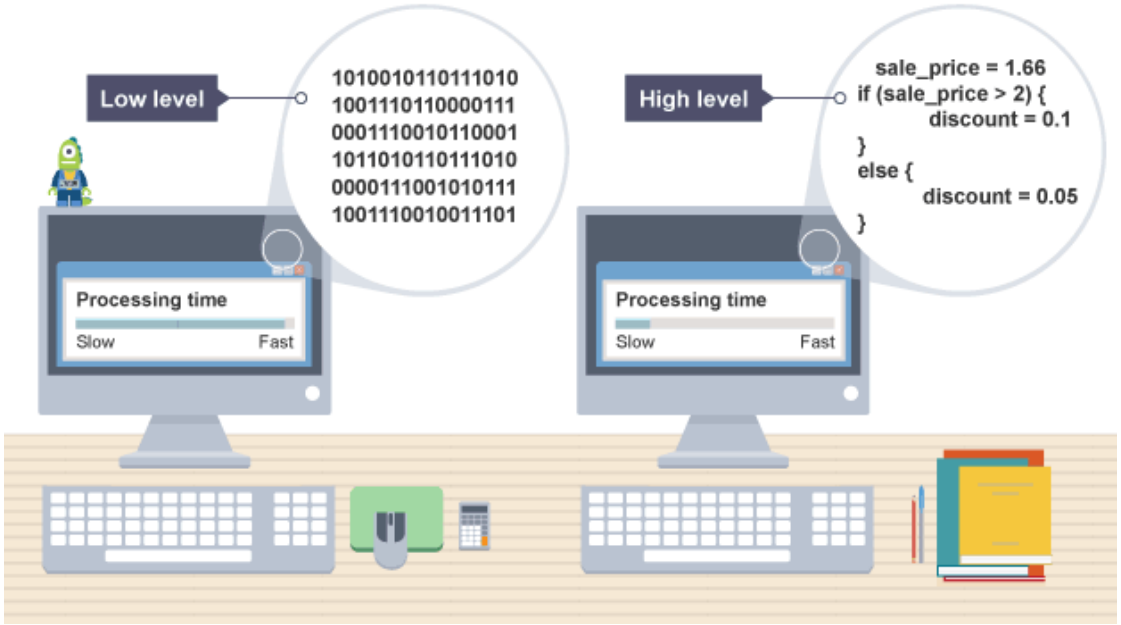

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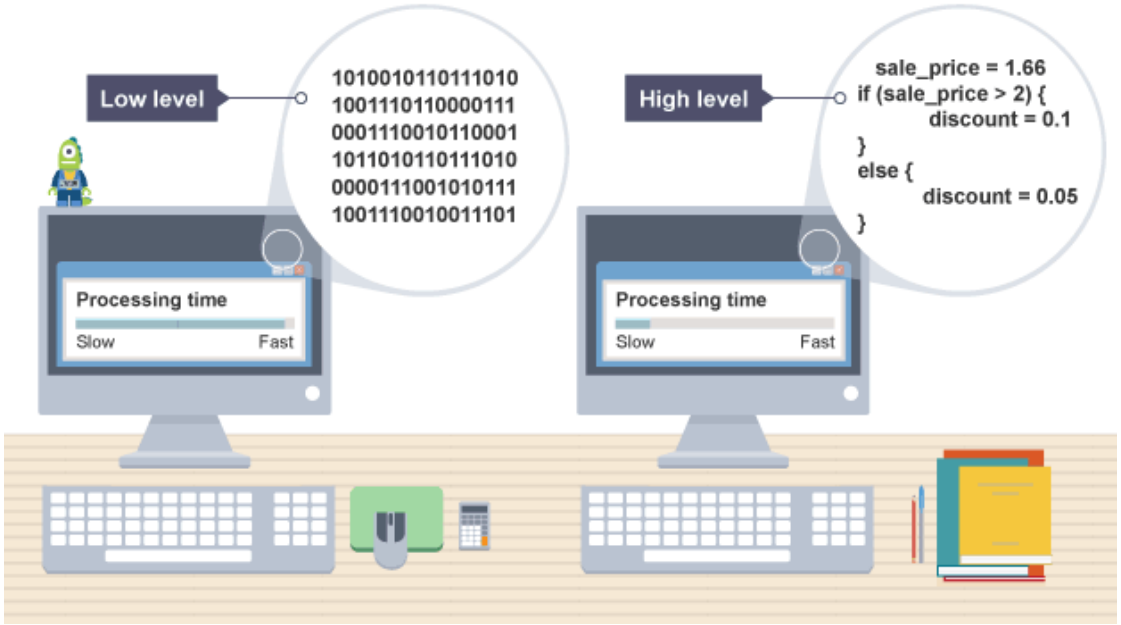

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- Programmers focused on the applications.
- Hardware Experts focused on compilers.
- High gains in productivity.
- "Democratization" of the software development.

Big Data and Machine Learning Ecosystem

Claire D. Costa. Best Python Libraries for Machine Learning and Deep Learning.
`https://towardsdatascience.com/best-python-libraries-for-machine-learning-and-deep-learning-b0bd40c7e8c`

Big Data and Machine Learning Libraries:

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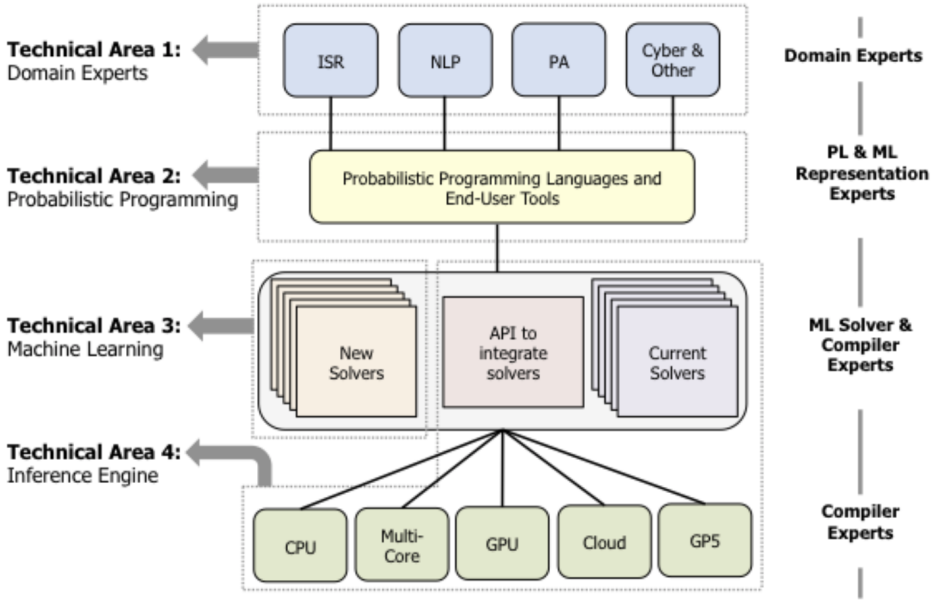
- Increase the **adoption** of these technologies.

What about in Probabilistic AI?

Which are the "high-level libraries" in Probabilistic AI?

Why PPLs?



PPLs as high-level programming languages for **probabilistic machine learning systems**:

- Stacked architecture

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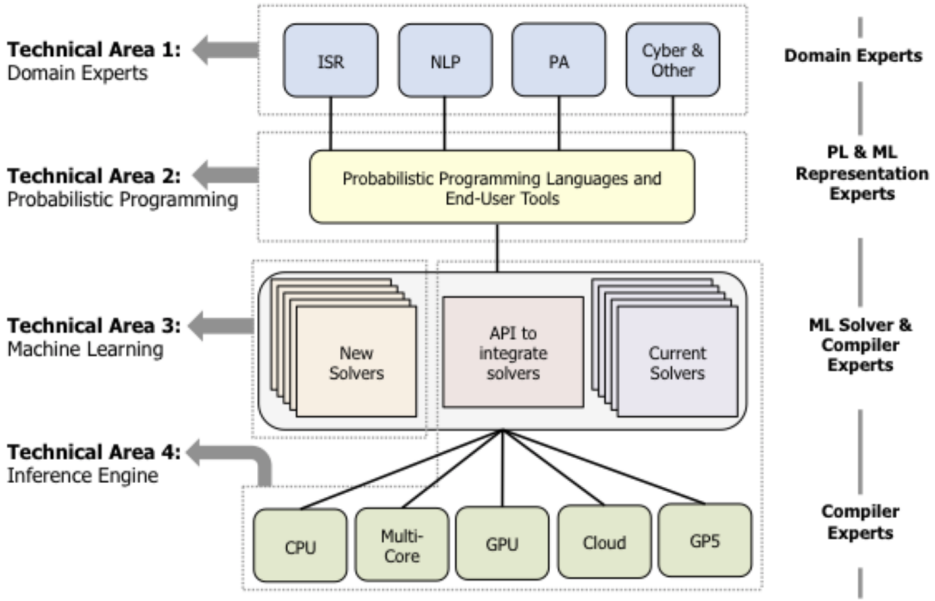

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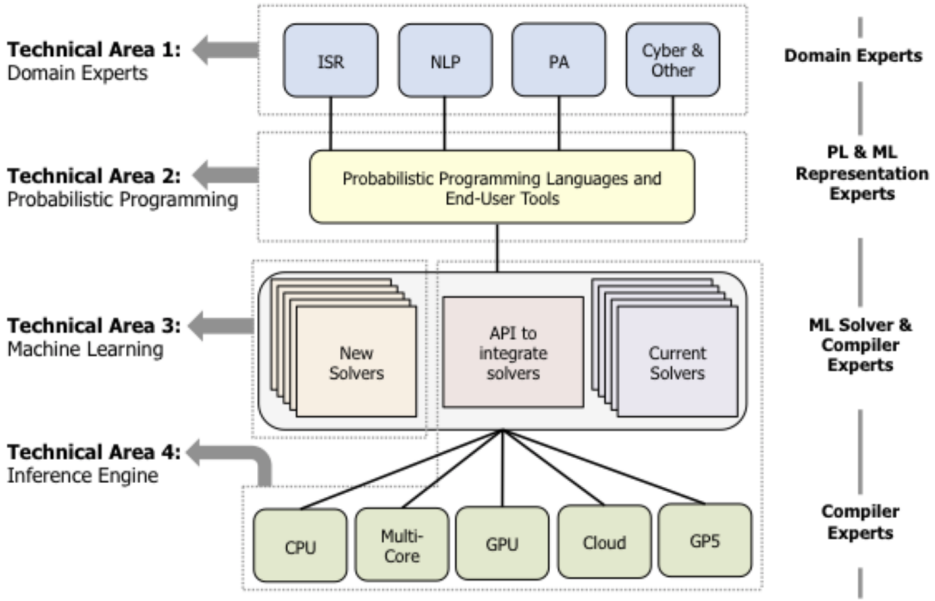

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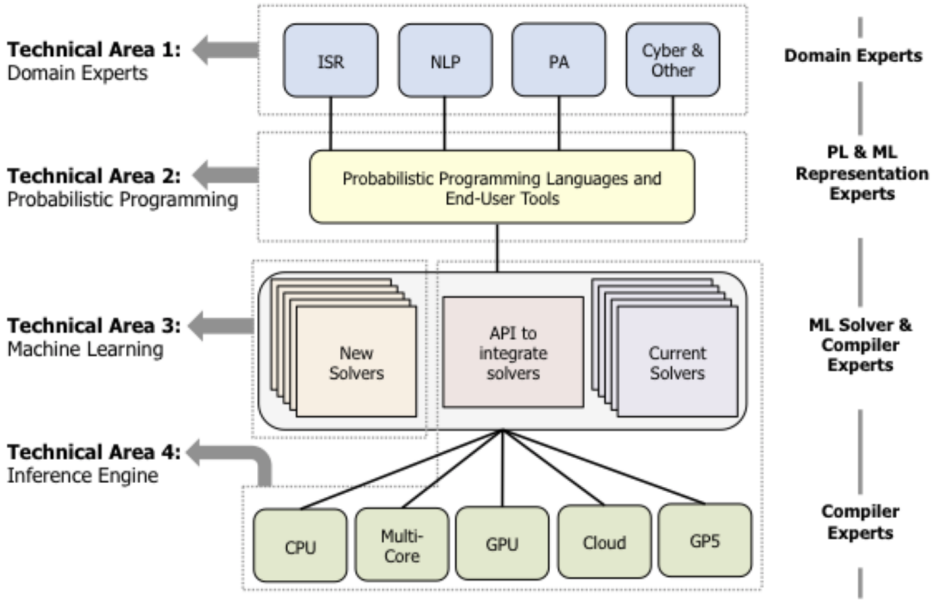

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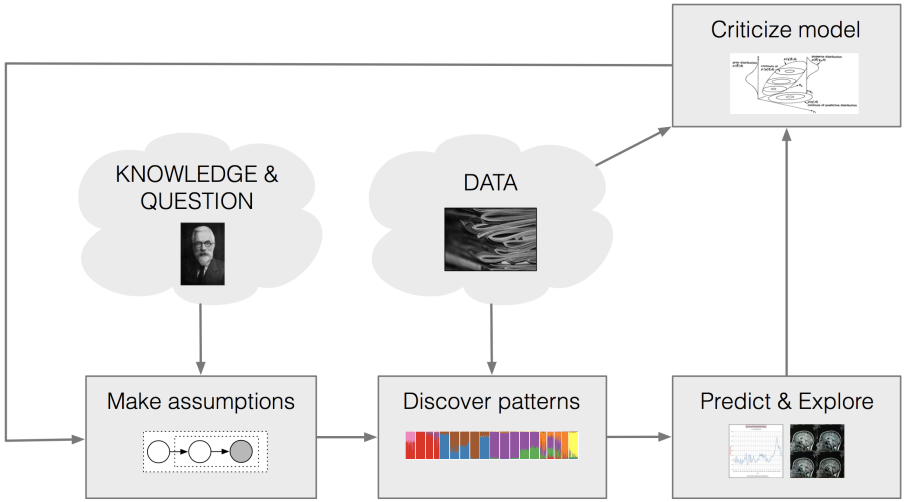
- Compile experts will focus on running these ML solvers on specialized hardware.

Box's Loop



[Box, 1980; Rubin, 1984; Gelman+ 1996; Blei, 2014]

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- Simplify probabilistic machine learning model code.

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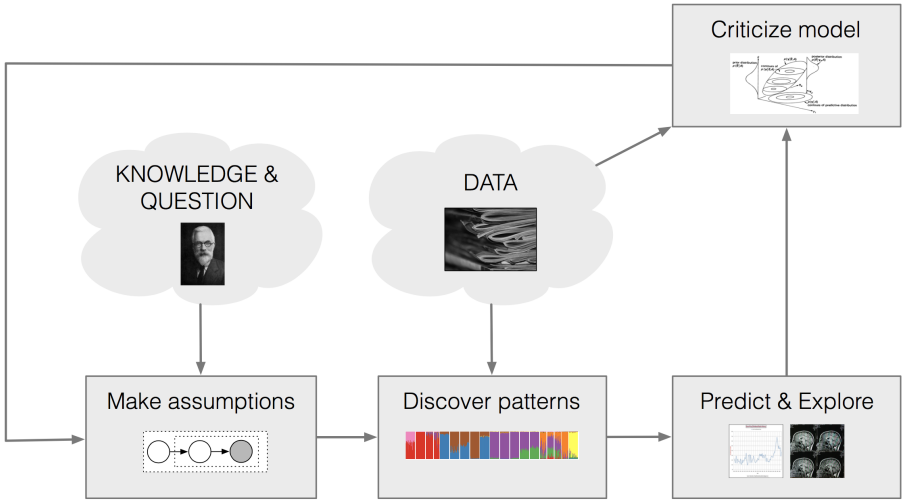

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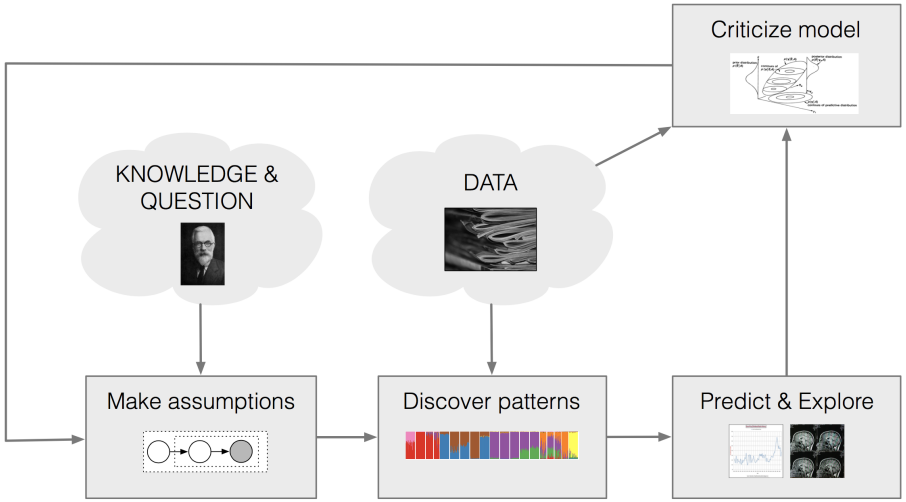

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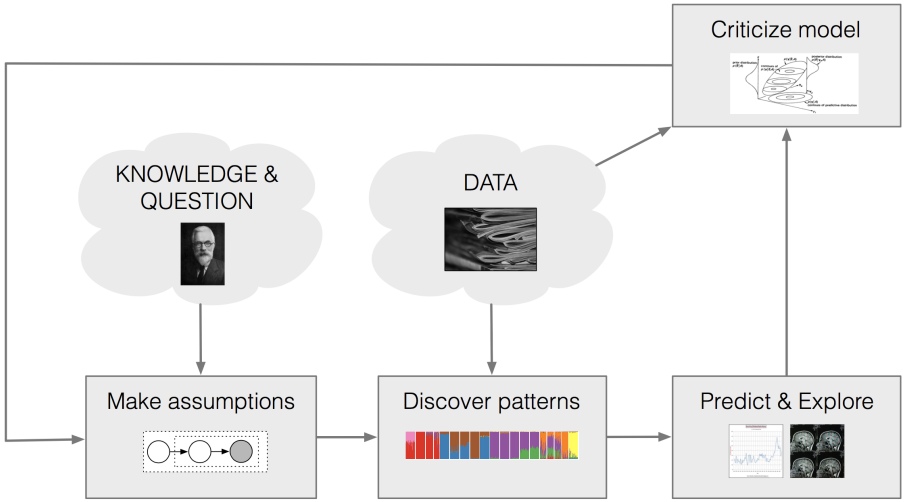

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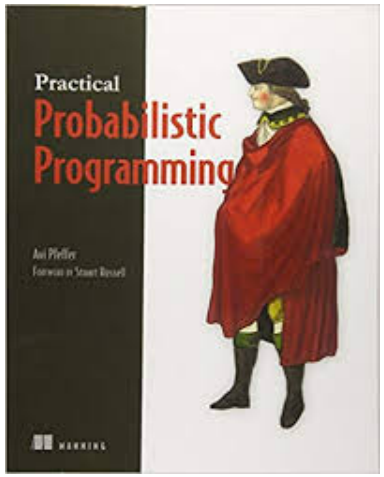
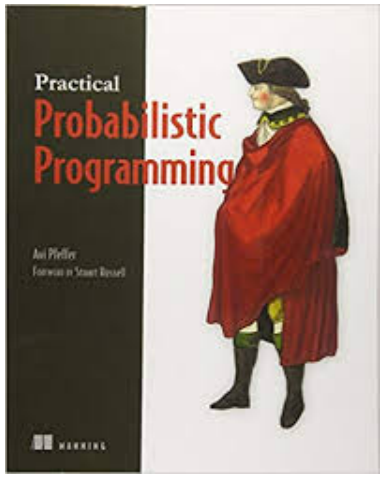


1st Generation of PPLs :

- Bugs, WinBugs, Jags, Figaro, etc.



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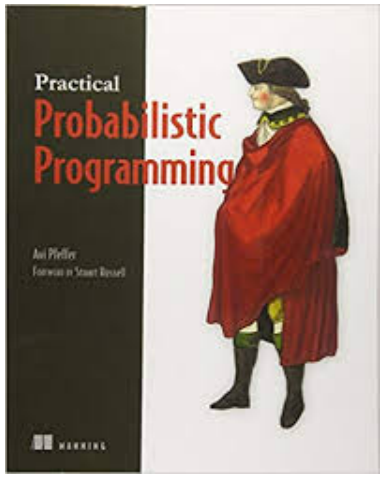

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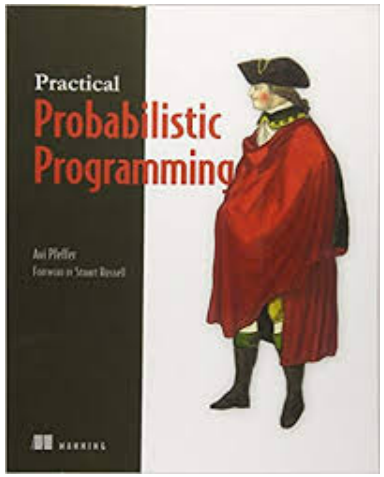

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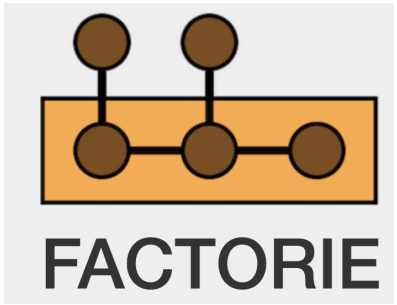

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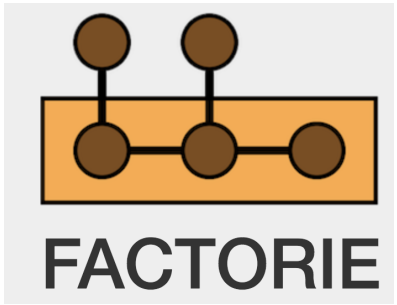

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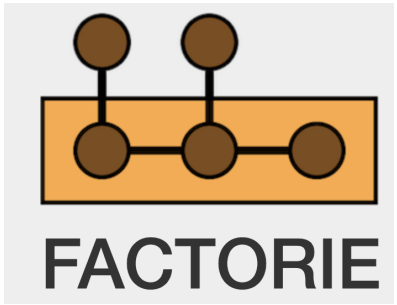

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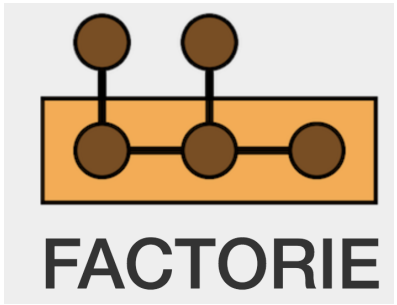

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- Restricted probabilistic model family (i.e. factor graphs, conjuage exponential family, etc.)

3rd Generation of PPLs :

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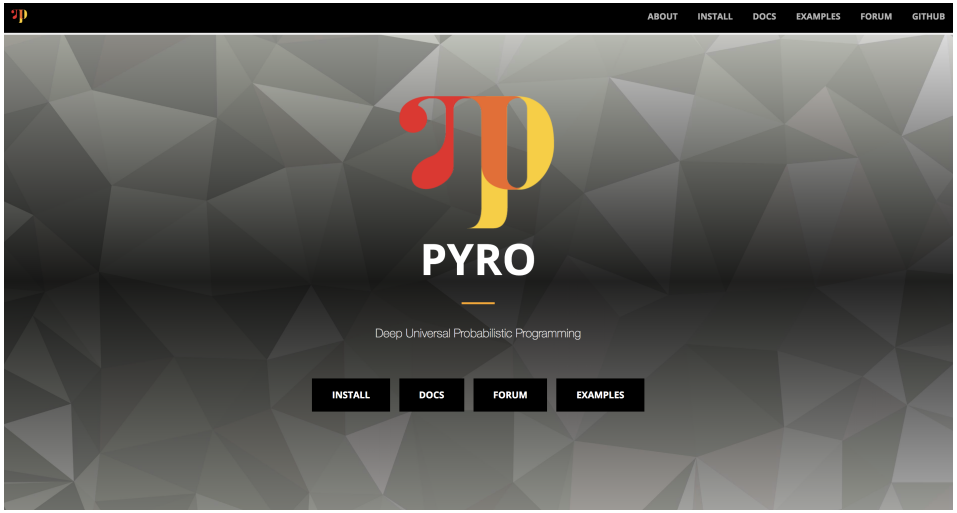
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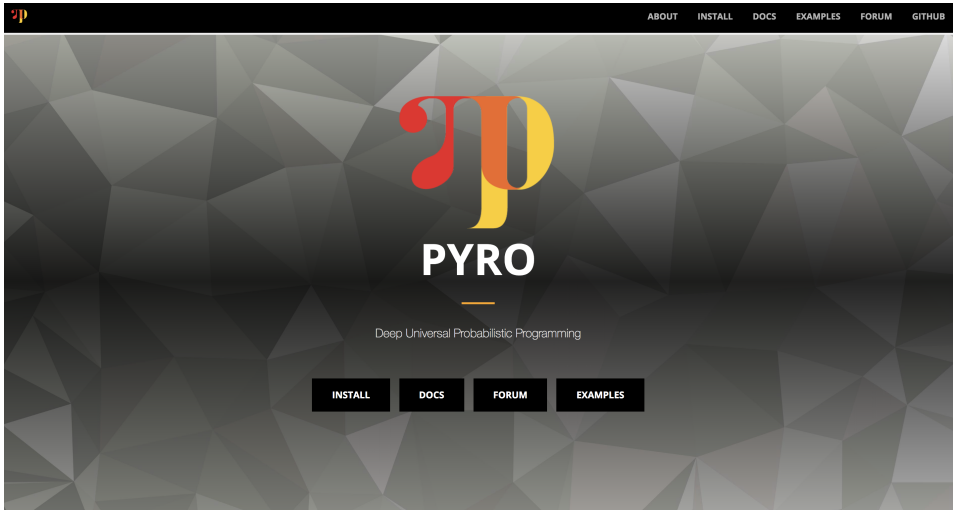

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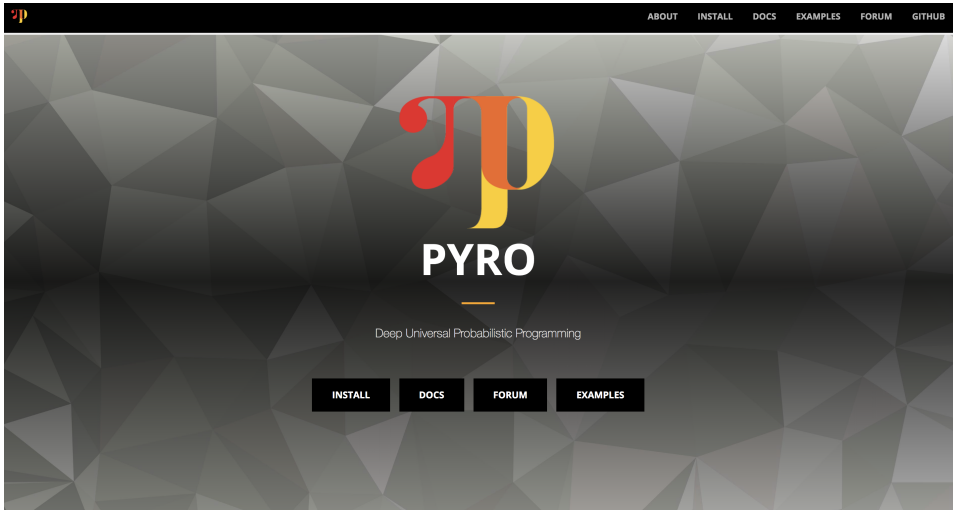

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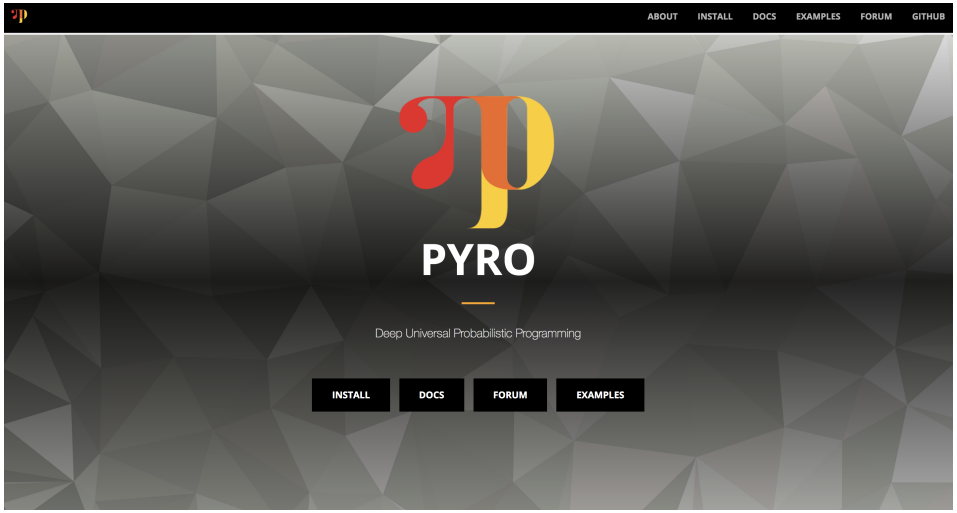

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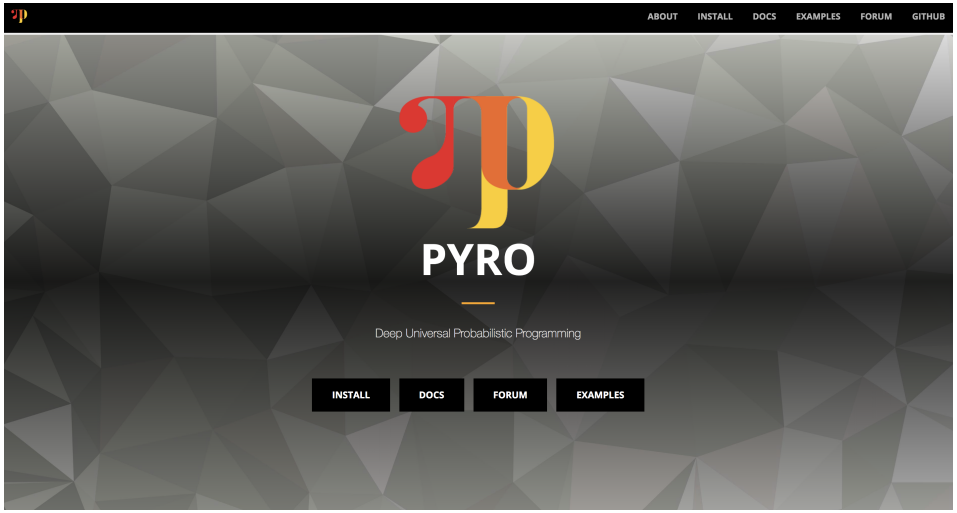

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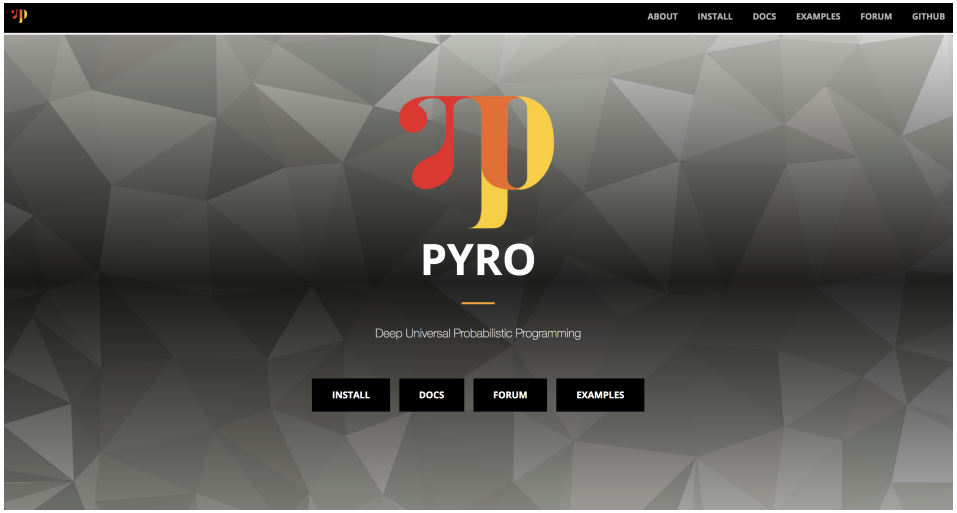

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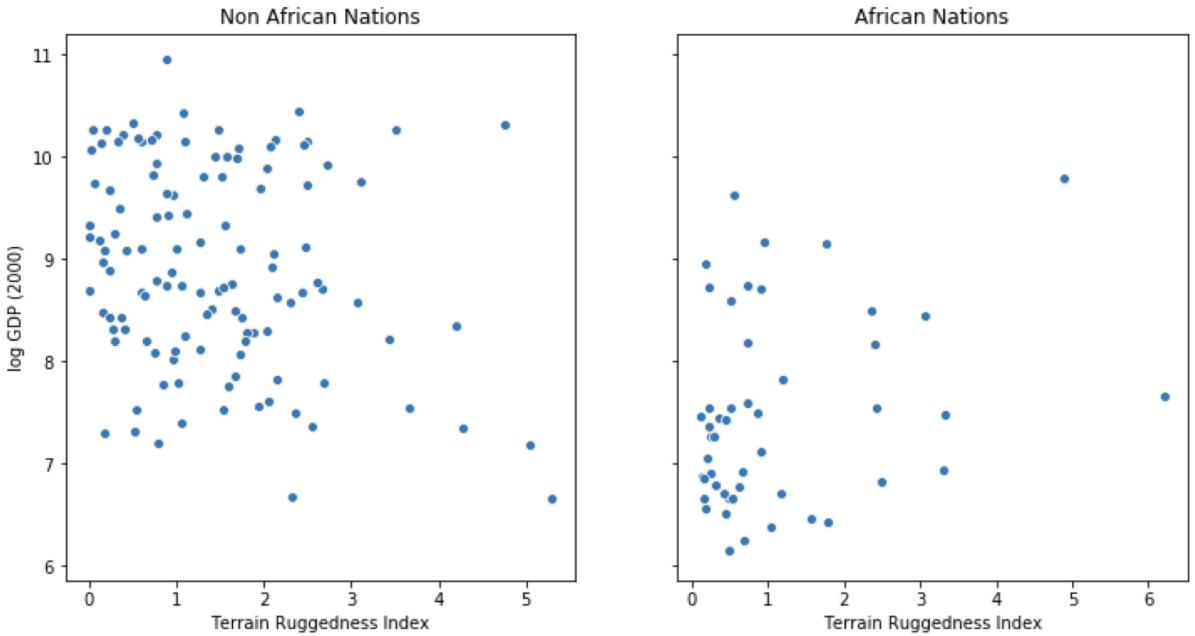
`https://github.com/PGM-Lab/probai-2021-pyro`

Bayesian linear regression

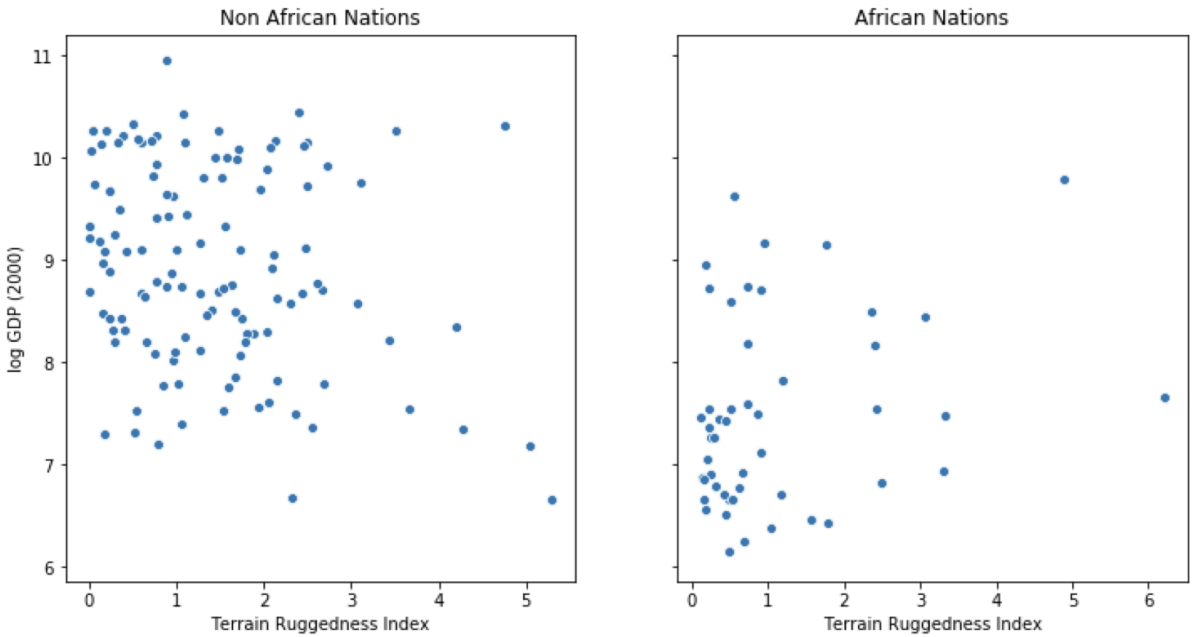
Real Data Example



Relationship between topographic heterogeneity and GDP per capita

- Terrain ruggedness or bad geography is related to poorer economic performance outside of Africa.

Real Data Example

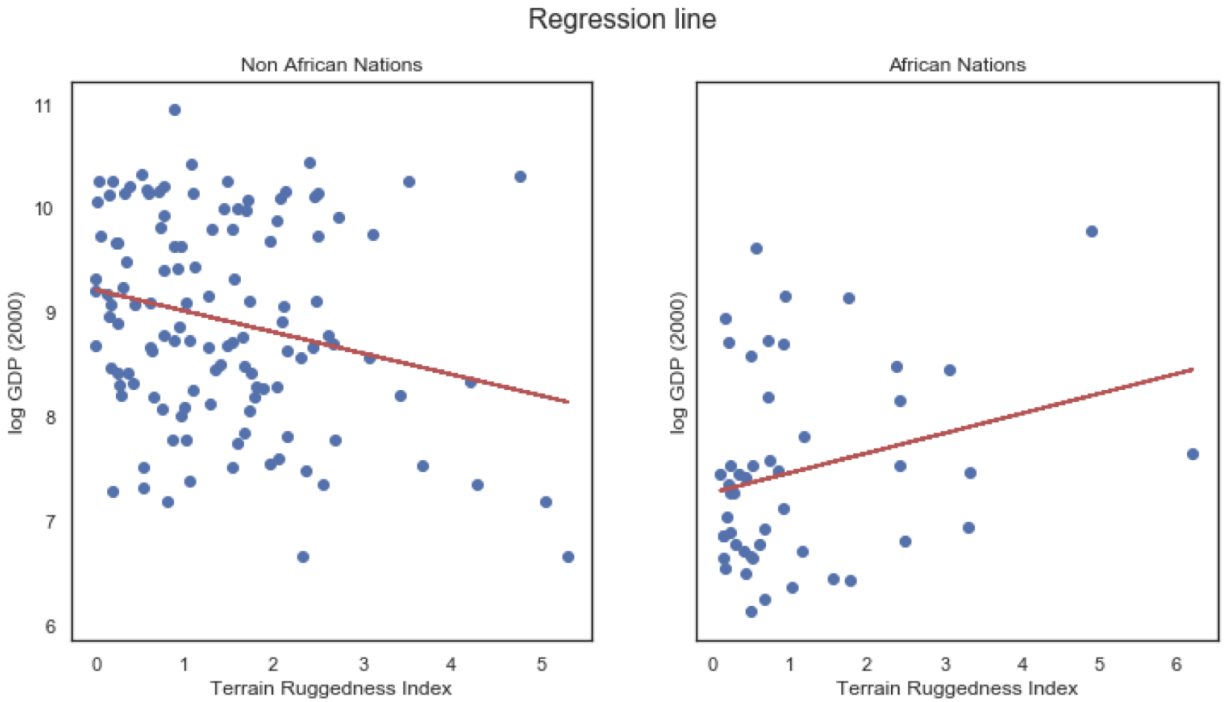


Relationship between topographic heterogeneity and GDP per capita

- Terrain ruggedness or bad geography is related to poorer economic performance outside of Africa.
- Rugged terrains have had a reverse effect on income for African nations.

Day1/bayesian_linear_regression.ipynb

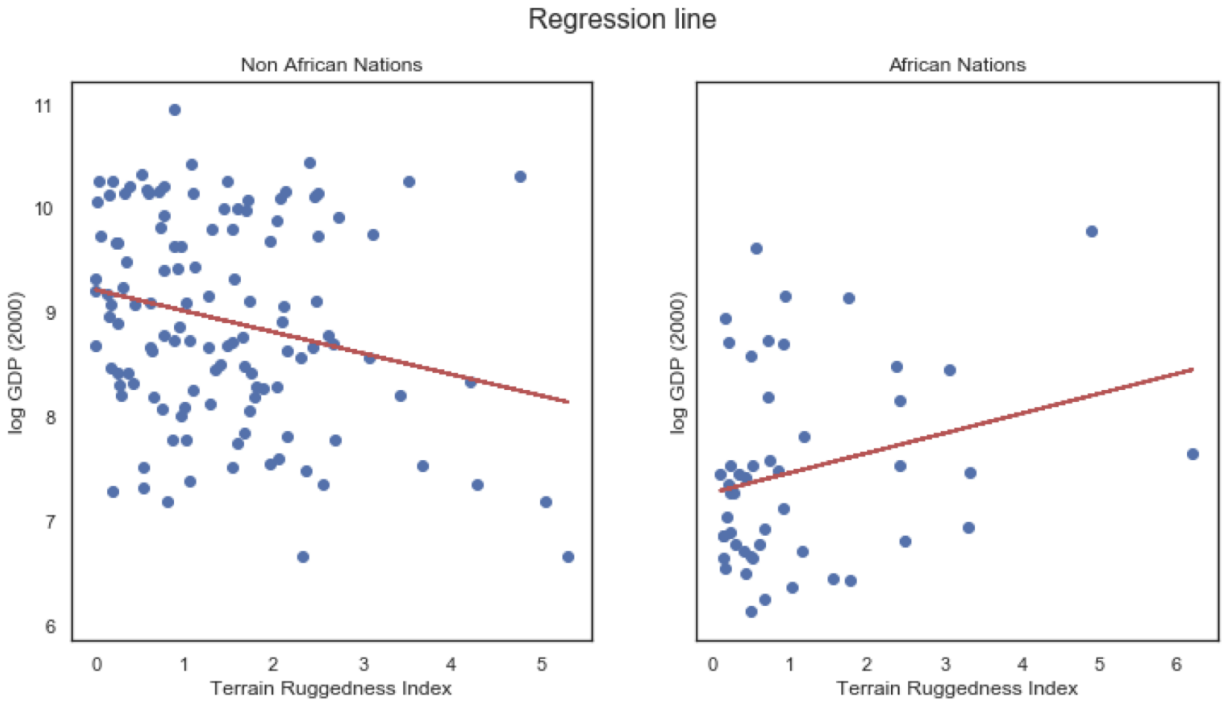
Real Data Example



Linear Regression Model

- Negative slope for Non African Nations.
- Positive slope for African Nations.

Real Data Example



Bayesian Linear Regression Model

- Modeling data noise (aleatoric uncertainty).
- Modeling uncertainty about the linear coefficients (epistemic uncertainty).