# AMiDST TOOLBOX

Probabilistic Machine Learning

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# OUTLINE

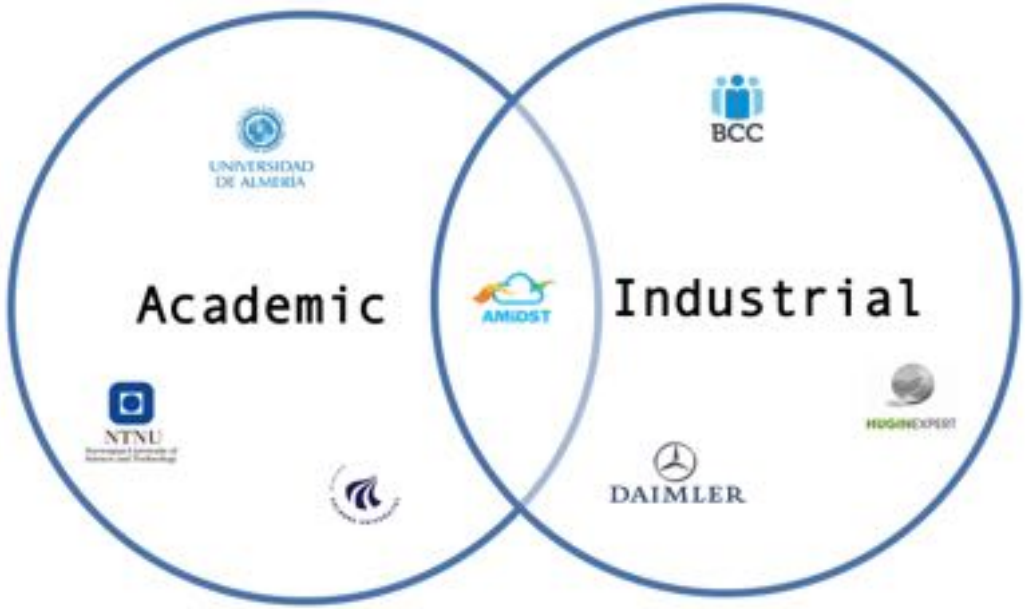
AMiDST TOOLBOX

- **Session 1**: Introduction to Probabilistic Machine Learning
  - Slides can be downloaded here.
- **Session 2**: Introduction to the AMIDST Toolbox.
  - Slides can be downloaded here.
  - Code exercises can be found here.
- **Session 3**: Coding an Intelligent Fire Detector System with the AMIDST Toolbox.
  - Slides can be downloaded here.
  - Code exercises can be found here.
- **Session 4**: Latent Variable Models.
  - Slides can be downloaded here.
- **Session 5**: Streaming data, Scalable Learning and Temporal Models with the AMIDST Toolbox.
  - Slides can be downloaded here.
  - Code exercises can be found here.
- **Session 6**: Future Trends in Probabilistic Machine Learning.
  - Slides can be downloaded here.

https://github.com/andresmasegosa/GeiloWinterSchool2018

# THE AMIDST CONSORTIUM





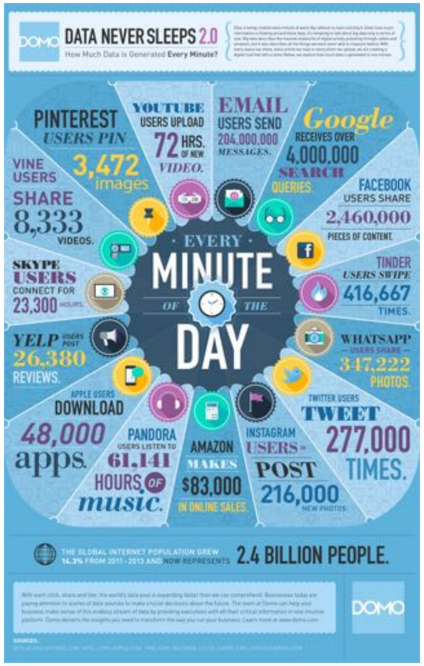


Let it burn!
It’s a shameful memory

$3^{rd}$ century BC

50 thousands papyrus = 20 thousands books

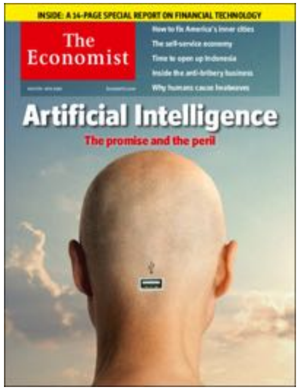
# 21$^{st}$ century DC




*6 thousand books, 2 millions posts and news daily*


The Economist
Obama the warrior
Misgoverning Argentina
The economic shift from West to East
Genetically modified crops blossom
The right to eat cats and dogs
The data deluge
AND HOW TO HANDLE IT: A 14-PAGE SPECIAL REPORT

# *Machine Learning*



# Text Modelling

| 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|
| Game | Life | Film | Book | Wine |
| Season | Know | Movie | Life | Street |
| Team | School | Show | Books | Hotel |
| Coach | Street | Life | Novel | House |
| Play | Man | Television | Story | Room |
| Points | Family | Films | Man | Night |
| Games | Says | Director | Author | Place |
| Giants | House | Man | House | Restaurant |
| Second | Children | Story | War | Park |
| Players | Night | Says | Children | Garden |

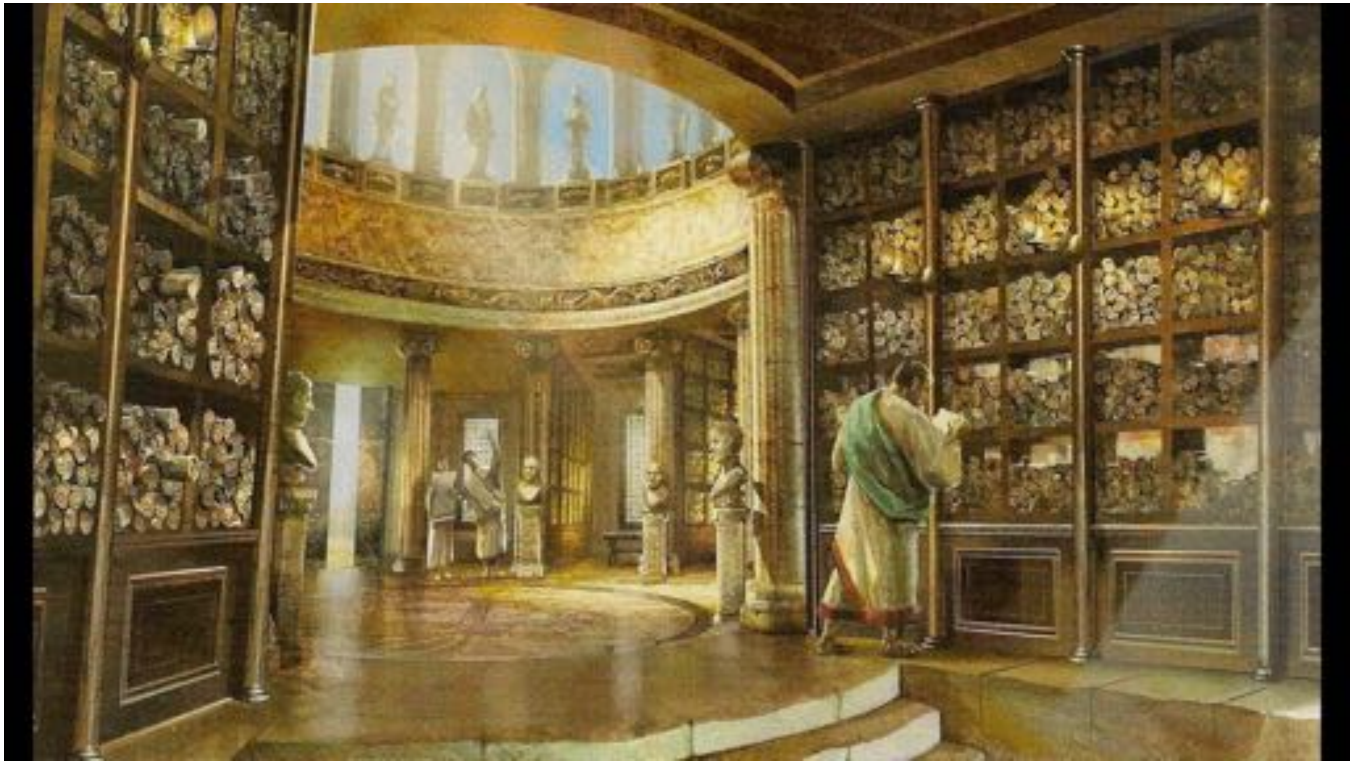
| 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|
| Bush | Building | Won | Yankees | Government |
| Campaign | Street | Team | Game | War |
| Clinton | Square | Second | Mets | Military |
| Republican | Housing | Race | Season | Officials |
| House | House | Round | Run | Iraq |
| Party | Buildings | Cup | League | Forces |
| Democratic | Development | Open | Baseball | Iraqi |
| Political | Space | Game | Team | Army |
| Democrats | Percent | Play | Games | Troops |
| Senator | Real | Win | Hit | Soldiers |

| 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|
| Children | Stock | Church | Art | Police |
| School | Percent | War | Museum | Yesterday |
| Women | Companies | Women | Show | Man |
| Family | Fund | Life | Gallery | Officer |
| Parents | Market | Black | Works | Officers |
| Child | Bank | Political | Artists | Case |
| Life | Investors | Catholic | Street | Found |
| Says | Funds | Government | Artist | Charged |
| Help | Financial | Jewish | Paintings | Street |
| Mother | Business | Pope | Exhibition | Shot |

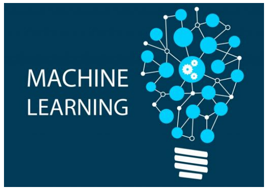
Topics found in 1.8M articles from the New York Times

[Hoffman, Blei, Wang, Paisley, JMLR 2013]

# Knowledge Access (3rd century BC)



# Knowledge Access (21$^{rd}$ century)




TensorFlow NumPy AMiDST TOOLBOX

# What is Machine Learning?

*Manual Computer Programming*

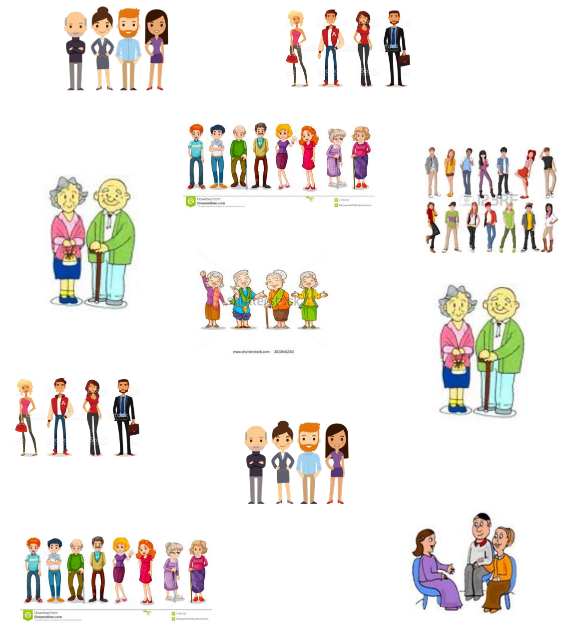
*vs*

# What is Machine Learning?



*Automatic Computer Programming*

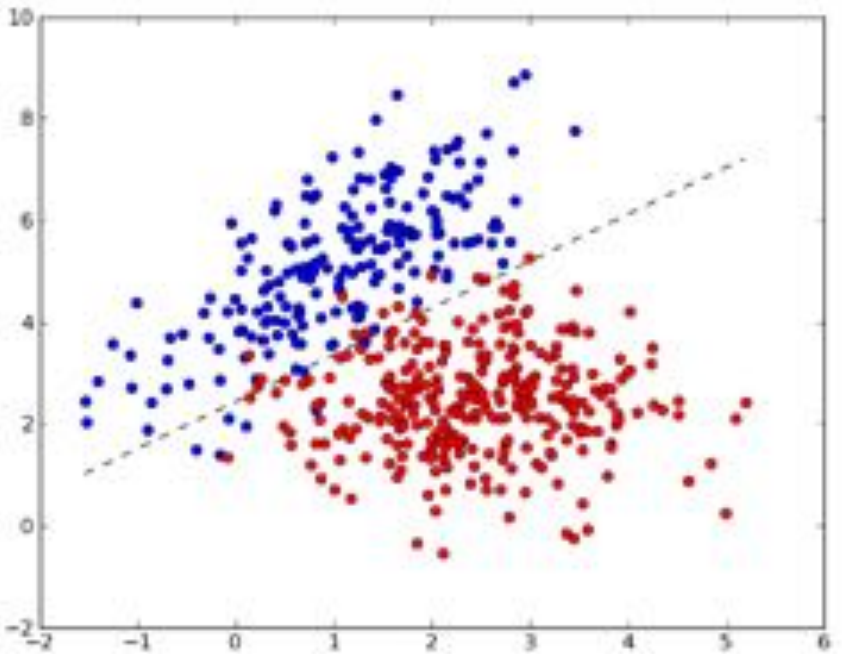
*vs*



# Supervised Learning

AMIDST TOOLBOX

- Finding a functional mapping:




$$f_\theta : X \rightarrow Y$$

$$x \in \Re^2 \qquad y \in \{Red, Blue\}$$

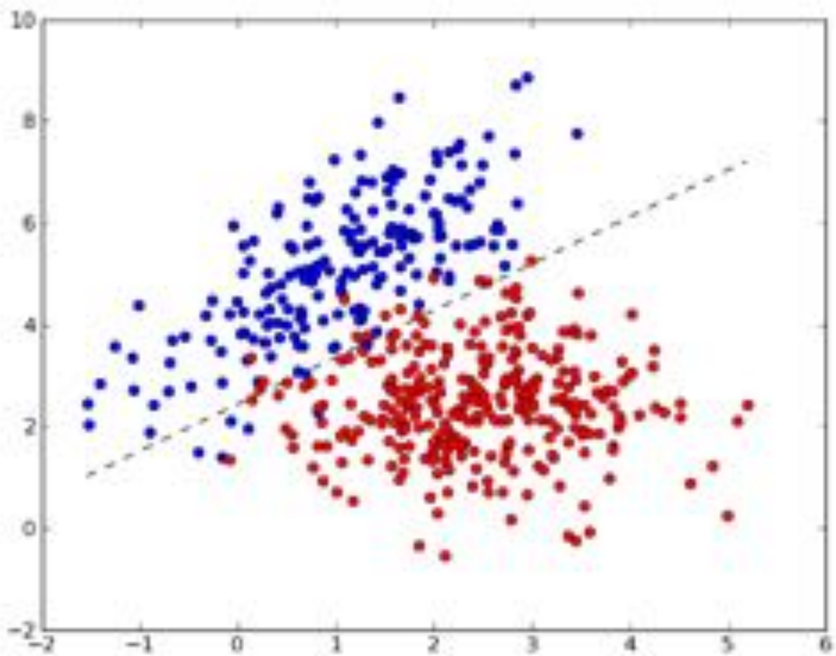
$$f(x;\theta) = \begin{cases} Blue & \theta^T x \geq 0 \\ Red & \theta^T x < 0 \end{cases}$$

$$\theta \in \Re^2$$

The mapping problem reduces to find the suitable $\theta^\star$ .

- How do we find $\theta^\star$ ?
  - We learn it from data!

$$f_\theta : X \to Y$$

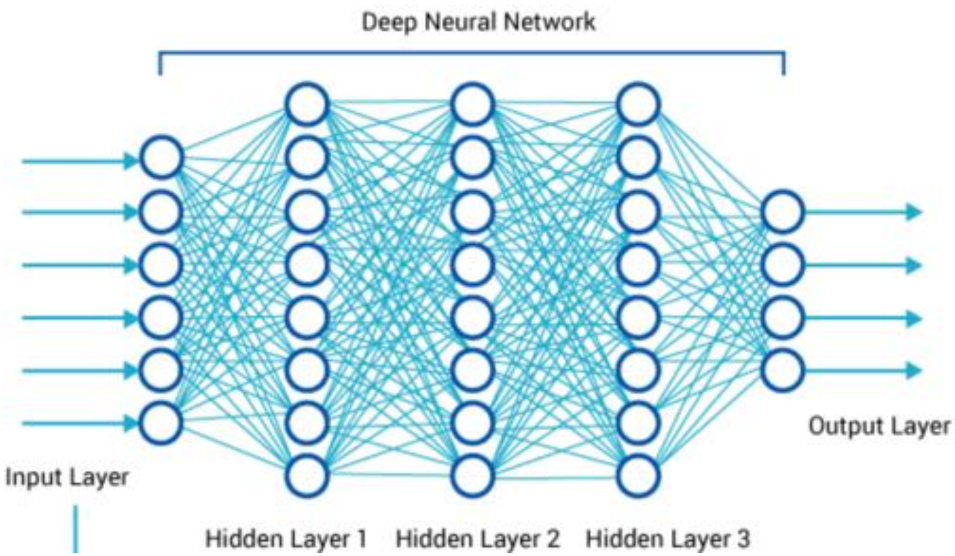



$$\mathcal{D} = \{(x_1, y_1), \ldots, (x_n, y_n)\}$$

$$\ell((x_i, y_i); \theta) = \begin{cases} 0 & f(x_i; \theta) = y_i \\ 1 & f(x_i; \theta) \neq y_i \end{cases}$$

$$\theta^\star = \arg\min_\theta \sum_{i=1}^{n} \ell((x_i, y_i); \theta)$$

Machine learning involves solving continuous optimization problems

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**DNN are highly non-linear mappings**

Andrew Ng: Artificial Intelligence is the New Electricity.
https://www.youtube.com/watch?v=21EiKfQYZXc&t=1206s

# SUPERVISED LEARNING

**X (Input)** —[Functional Mapping]→ **Y (Output)**

- Email → Spam? (0/1)
- Image → Object (computer vision)
- Audio → Text (speech recognition)
- English → French (automatic translation)
- (Corpus, Query) → List (information retrieval)
- (Ad, user) → Click? (Ad Placing)
- (Camera, Address) → Steering Angle, Brake Force,…. (Autonomous Driving)

Andrew Ng: Artificial Intelligence is the New Electricity.
https://www.youtube.com/watch?v=21EiKfQYZXc&t=1206s

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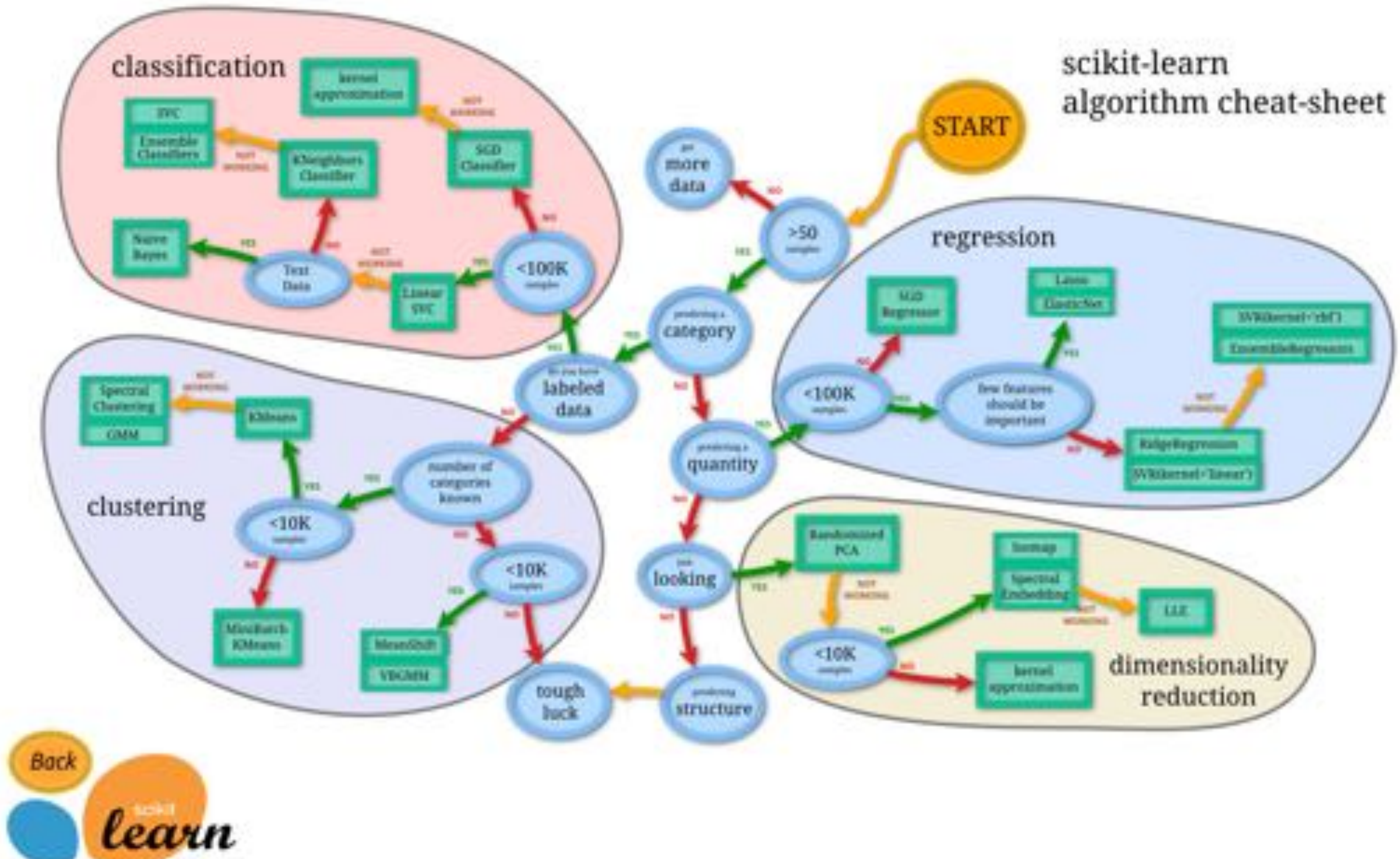
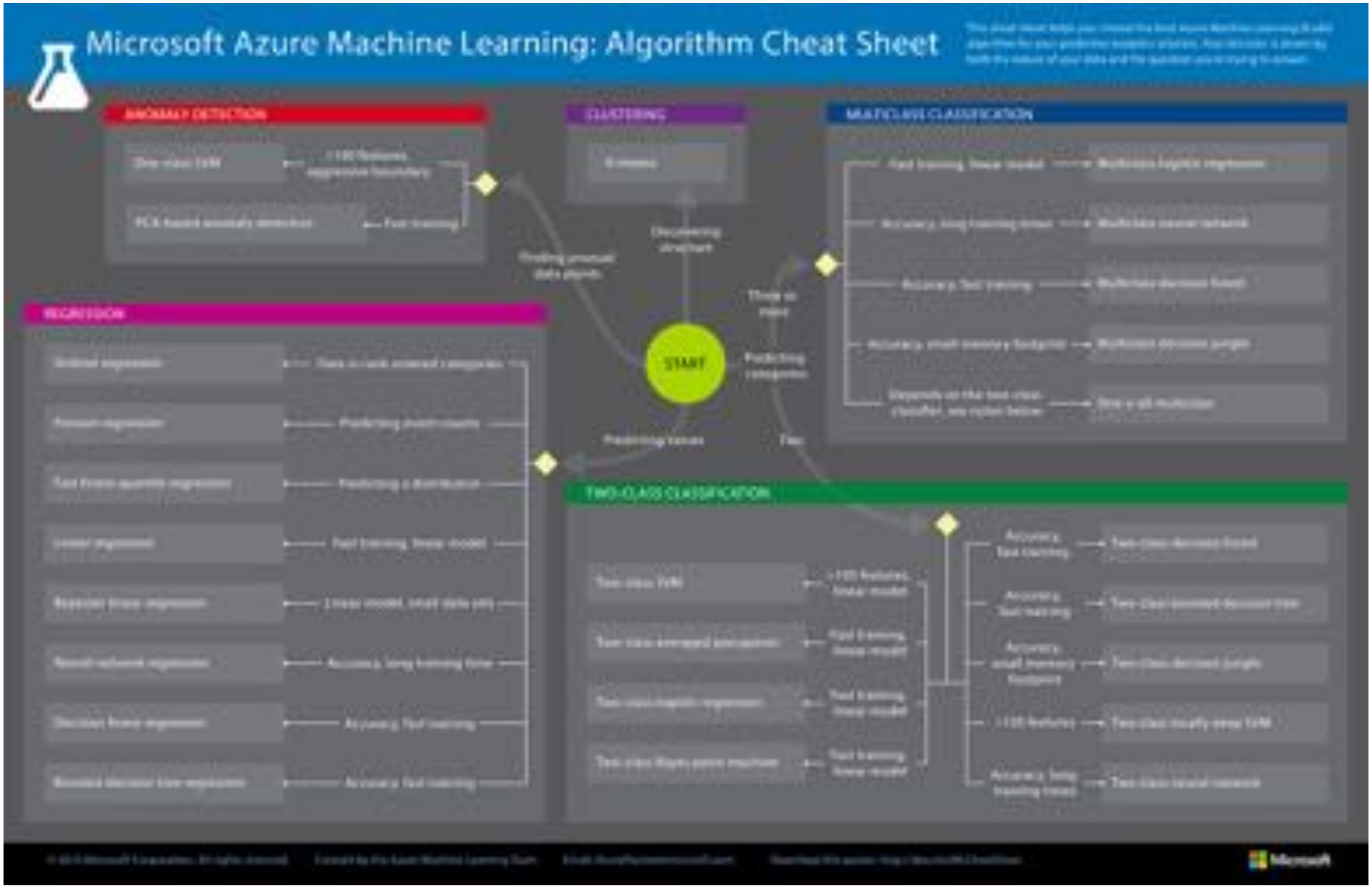
## Function-approximation Machine Learning




http://scikit-learn.org/stable/tutorial/machine_learning_map/index.html

# Machine Learning Landscape





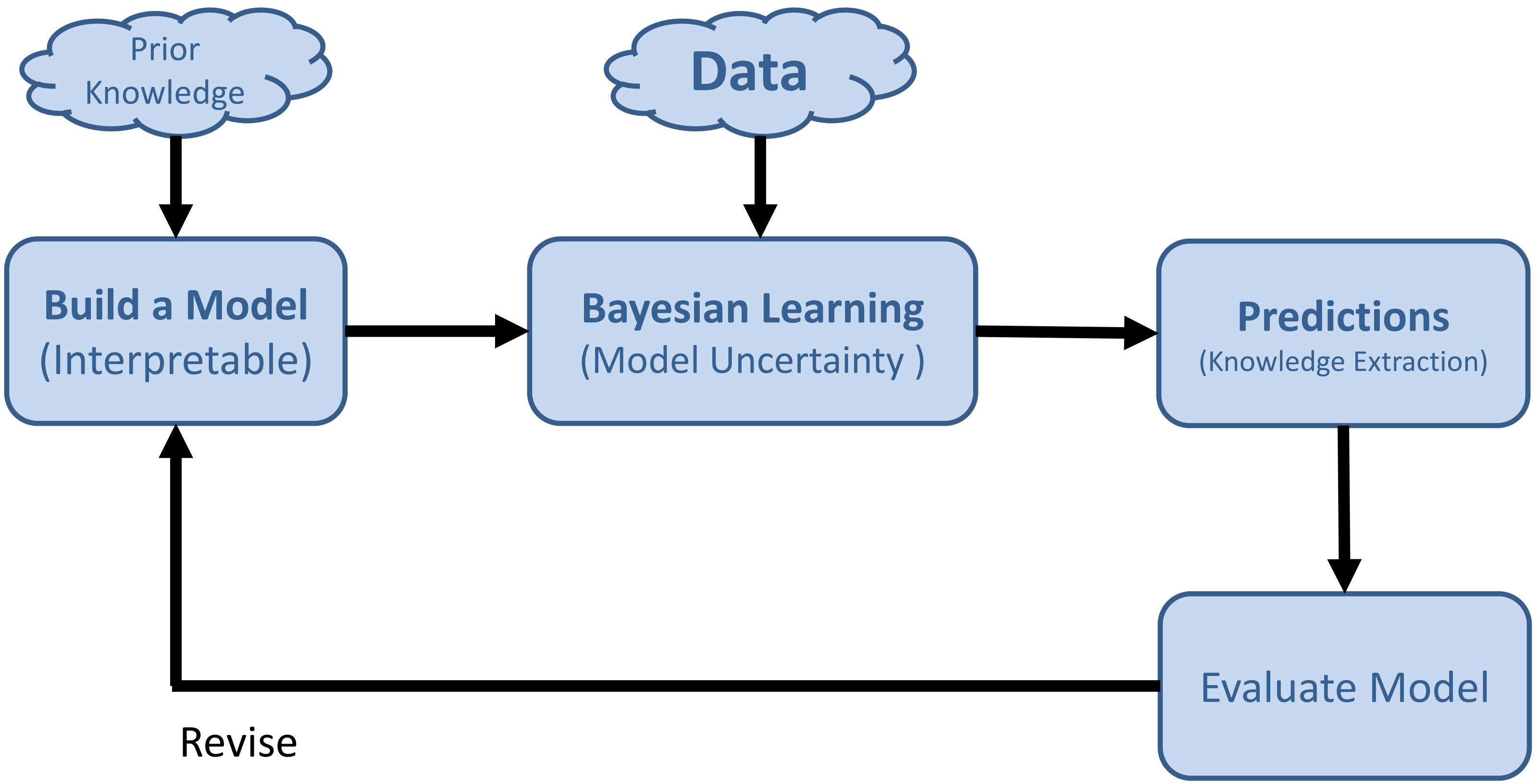
# Practical Issues

- High Cognitive Burden
  - Daunting number of algorithms and models.
  - Hard to master most of them.
- Algorithms can not be easily customized.
  - Real A.I. apps require ad-hoc adaptations.
  - Even Harder to adapt/modify existing algorithms.

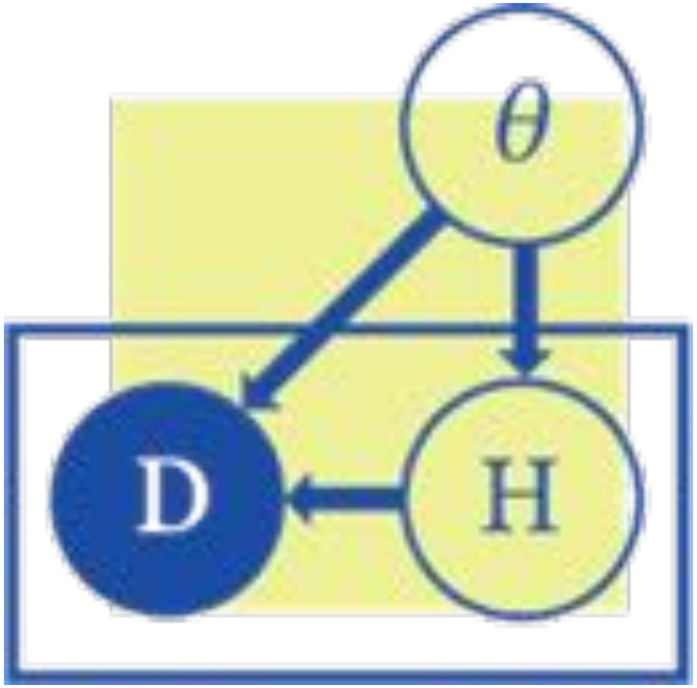
# Theoretical Issues

- Black Box Approaches
  - No Model Interpretability
  - No understanding in how decisions are made
- Uncertainty Quantification
  - No Predictions Uncertainty
  - No Model Uncertainty

# Probabilistic (Bayesian) Machine Learning

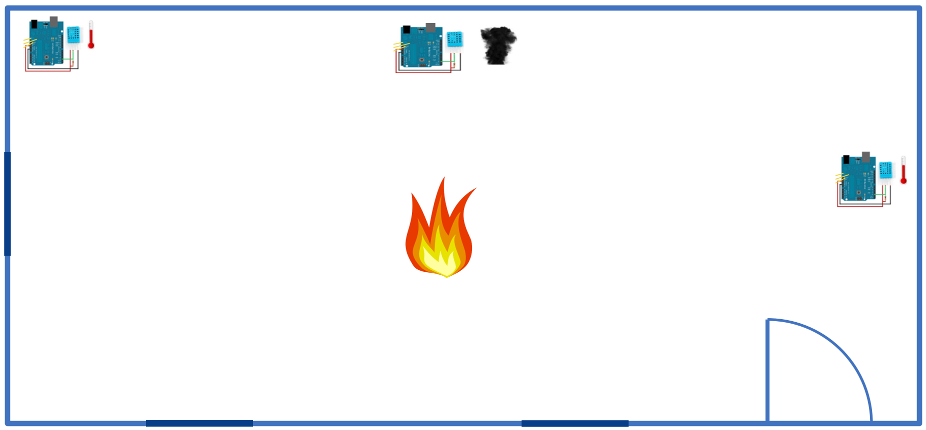



Blei, David M. "Build, compute, critique, repeat: Data analysis with latent variable models." *Annual Review of Statistics and Its Application* 1 (2014): 203-232.

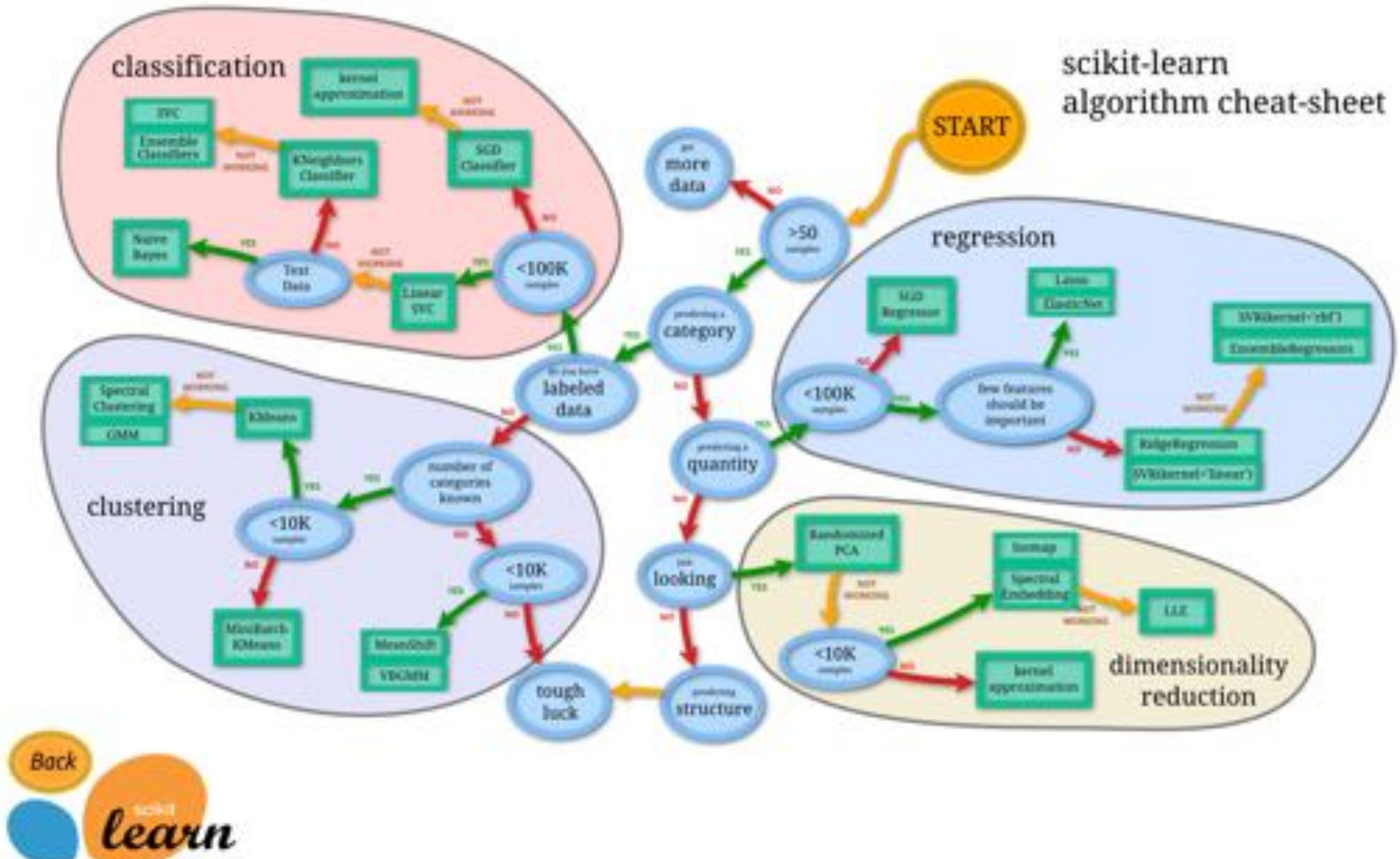

Probabilistic Graphical Models

## Fire Detection from smoke and temperature sensors



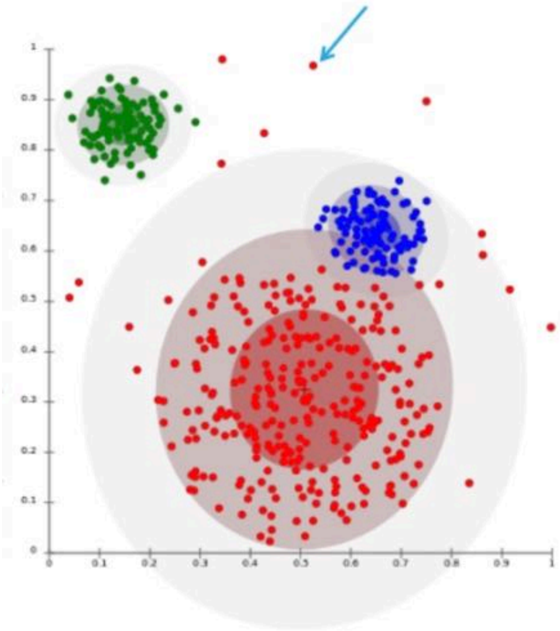
- Data Collected
  - Tons of observations in normal settings (no fire).
  - No observations in the presence of fire.

# Function-approximation Machine Learning



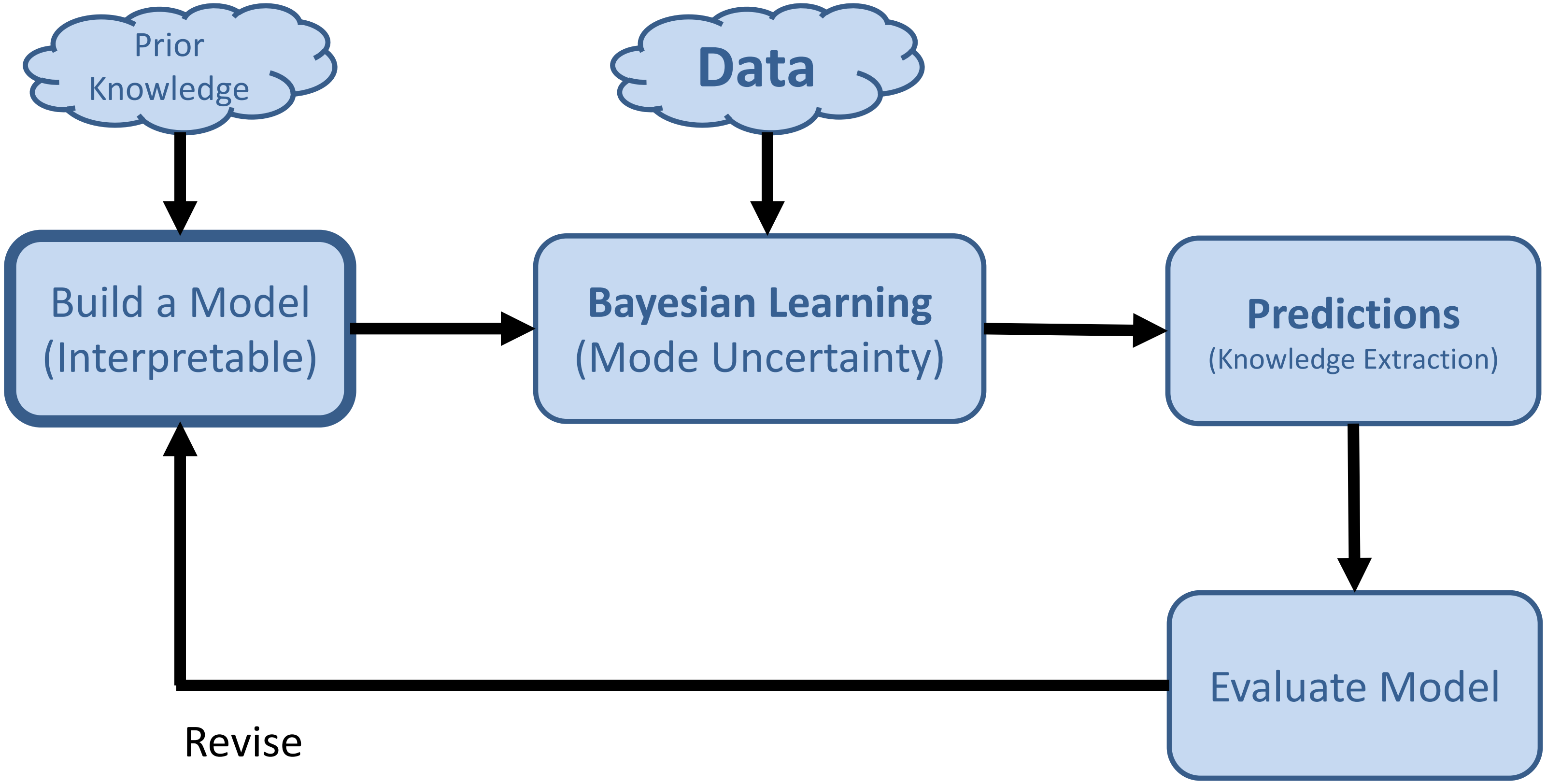

http://scikit-learn.org/stable/tutorial/machine_learning_map/index.html

# Fire Detector



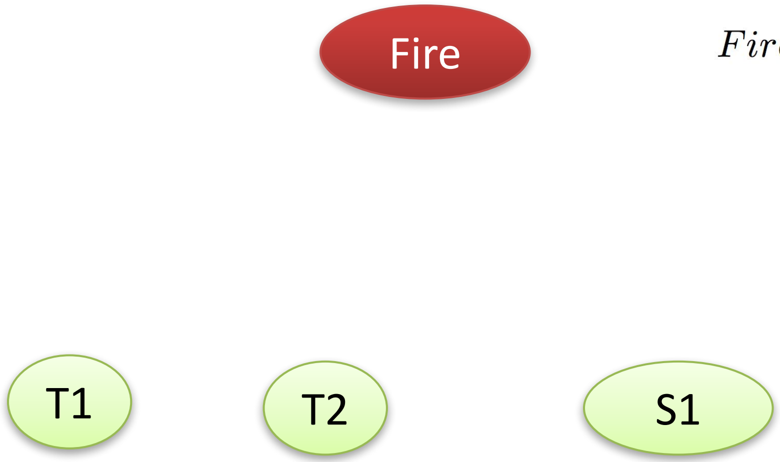
## Black Box Approach:

### Anomaly Detection with (streaming) K-means




Blei, David M. "Build, compute, critique, repeat: Data analysis with latent variable models." *Annual Review of Statistics and Its Application* 1 (2014): 203-232.

# Fire Detector Model




$$Fire \sim Binomial(\rho)$$

$$T1, T2 \sim Normal(\mu, \sigma)$$

$$S_1 \sim Binomial(\rho)$$

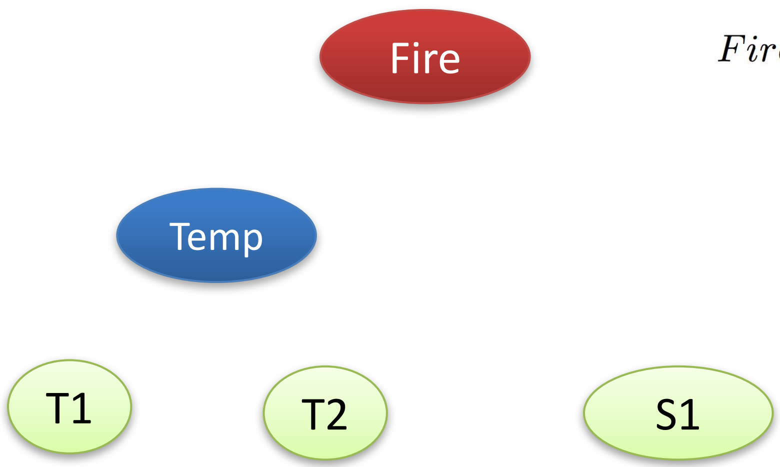
## Probabilistic Modeling

Every relevant object is a random variable.

# Fire Detector Model

$Fire \sim Binomial(\rho)$

$Temp \sim Normal(\mu, \sigma)$



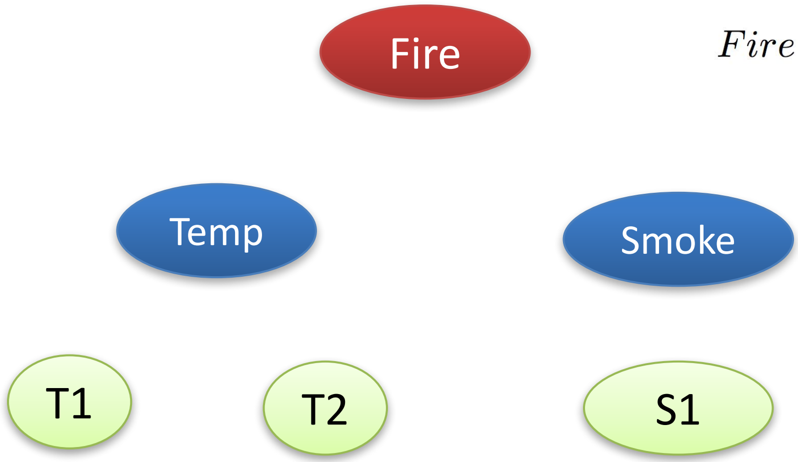

$T1, T2 \sim Normal(\mu, \sigma)$

$S_1 \sim Binomial(\rho)$

## Latent Variables

Non-observable relevant mechanisms

# FIRE DETECTOR MODEL




$Fire \sim Binomial(\rho)$

$Temp \sim Normal(\mu, \sigma)$

$Smoke \sim Binomial(\rho)$

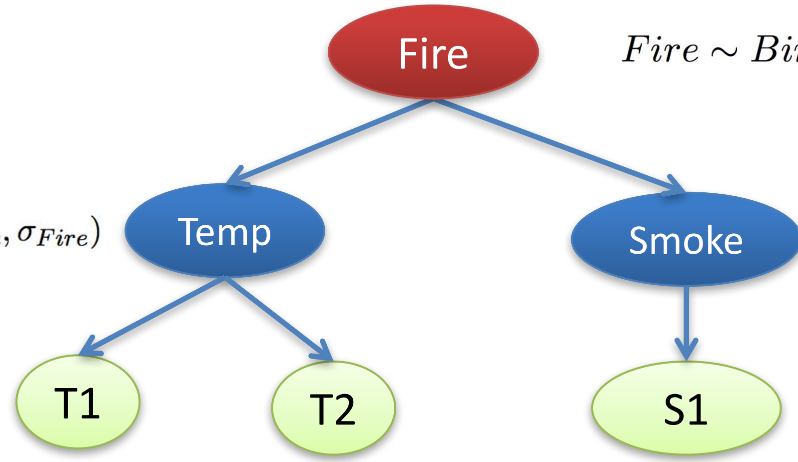
$T1, T2 \sim Normal(\mu, \sigma)$

$S_1 \sim Binomial(\rho)$

## Latent Variables

Non-observable relevant mechanisms

# FIRE DETECTOR MODEL




$Fire \sim Binomial(\rho)$

$Temp|Fire \sim Normal(\mu_{Fire}, \sigma_{Fire})$

$Smoke|Fire \sim Binomial(\rho_{Fire})$

$T1, T2|Temp \sim Normal(\mu_{Temp}, \sigma)$

$S_1|Smoke \sim Binomial(\rho_{Smoke})$

## Causal Relationships

They can be extracted for the mechanism itself

Code: Session3

# MODEL-BASED MACHINE LEARNING

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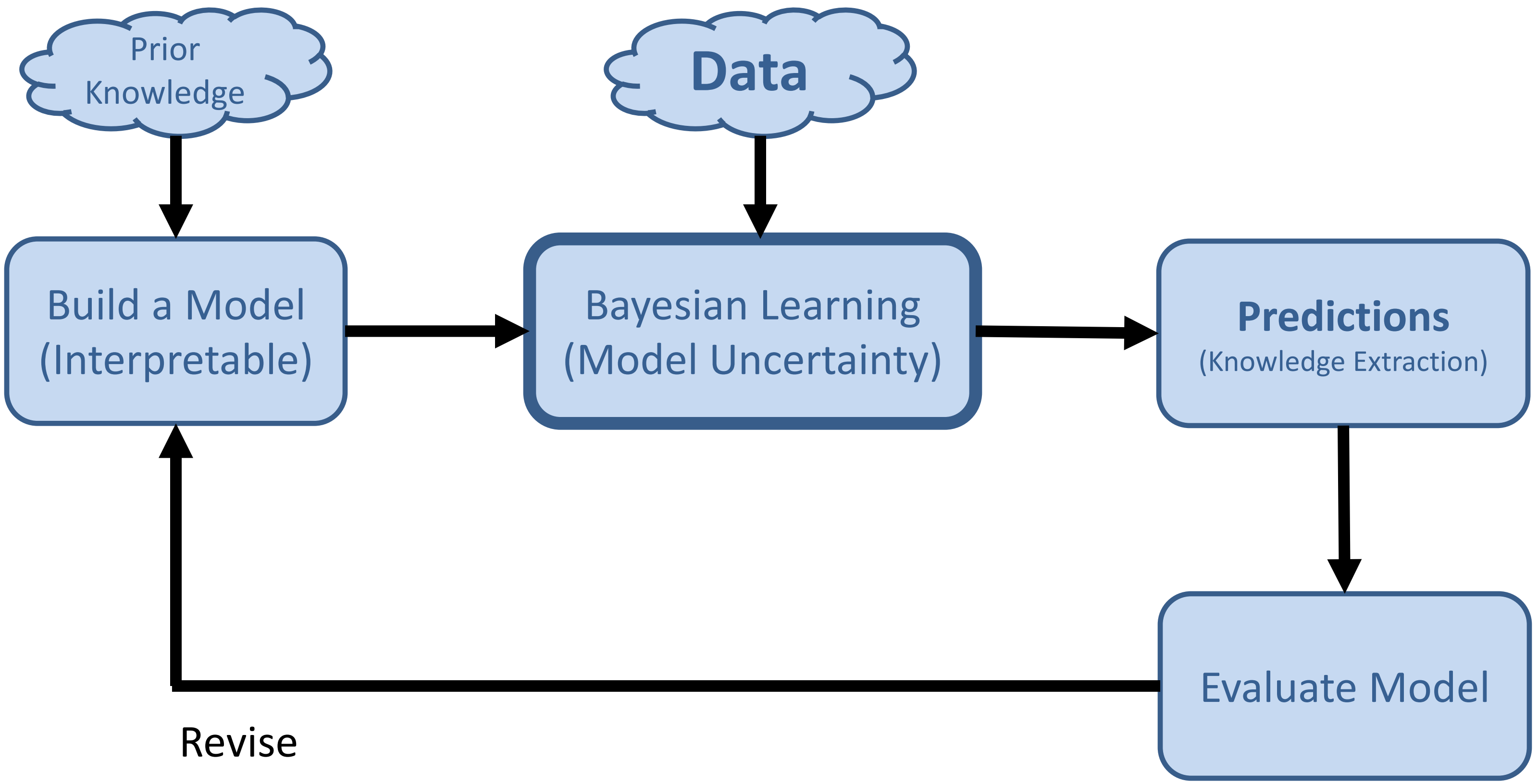


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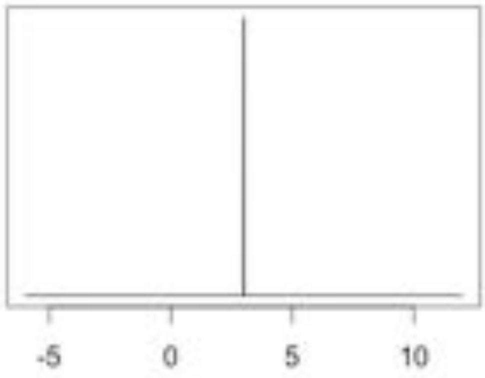
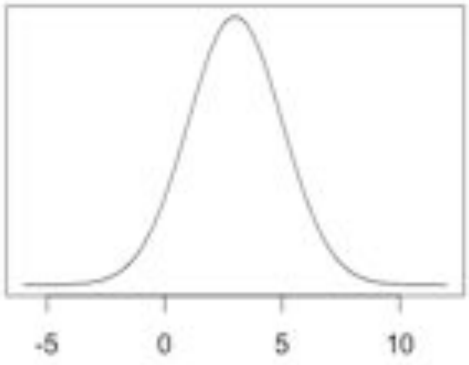
$$P(\theta|\mathbf{D})$$

## Bayesian Learning

# Model Uncertainty




vs



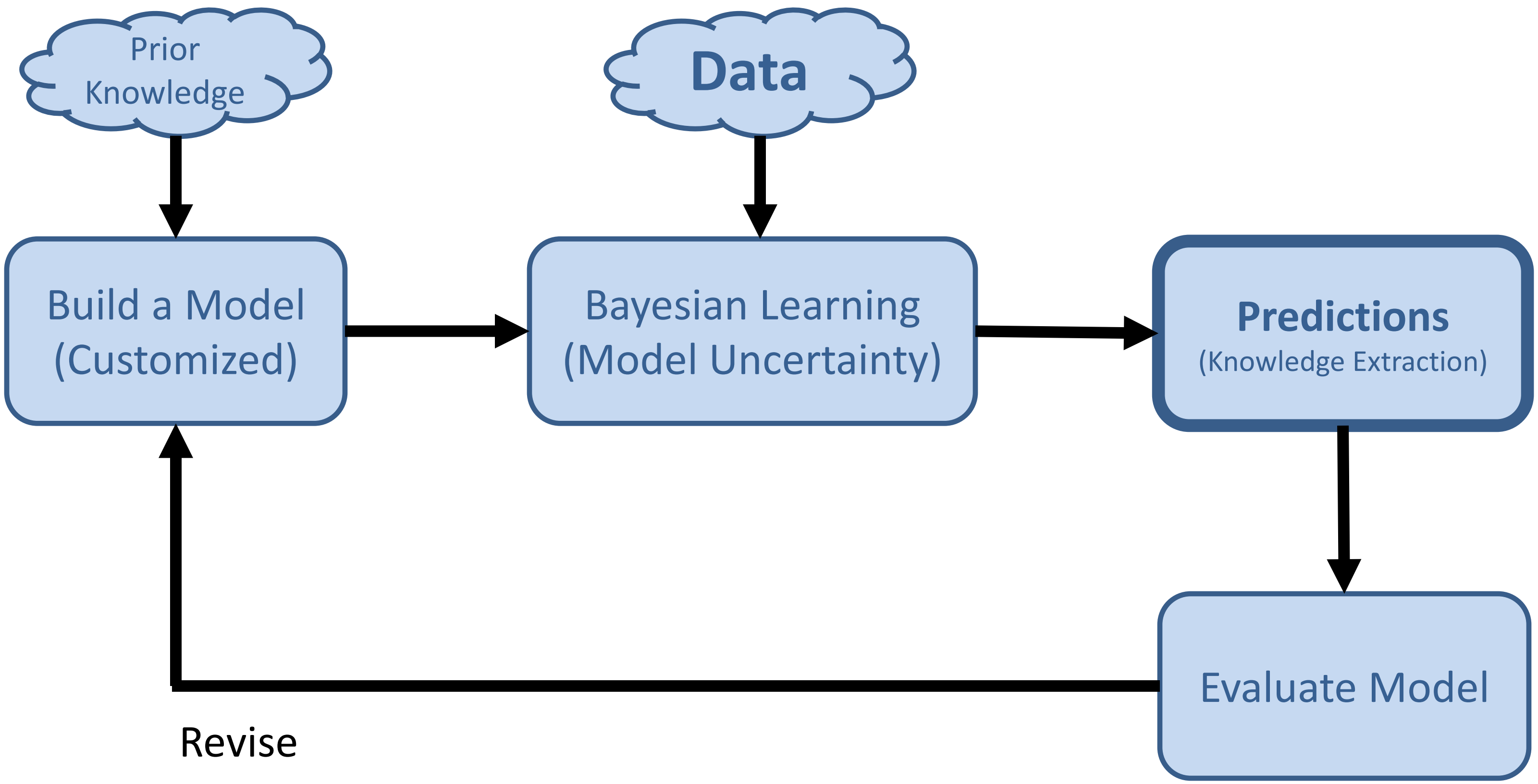

$$\theta^{\star}$$

[Point Estimate]

$$p(\theta|D)$$

[Bayesian Estimate]

Example: $y = \theta_0 + \theta_1 \cdot x_1 + \ldots + \theta_k \cdot x_k$

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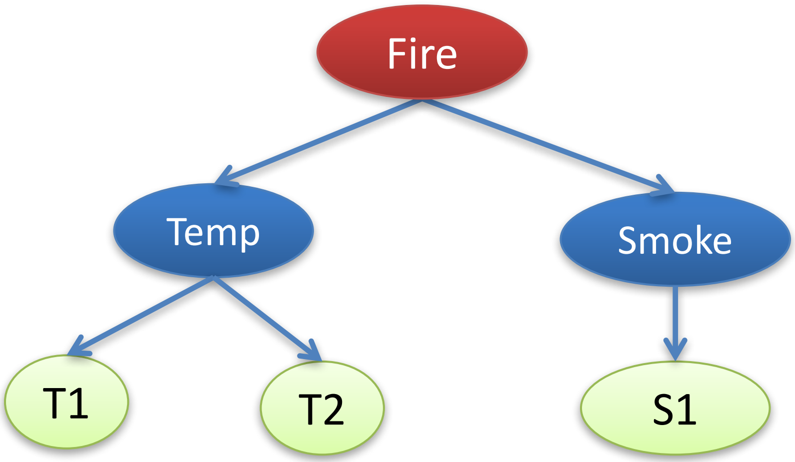
AMiDST TOOLBOX

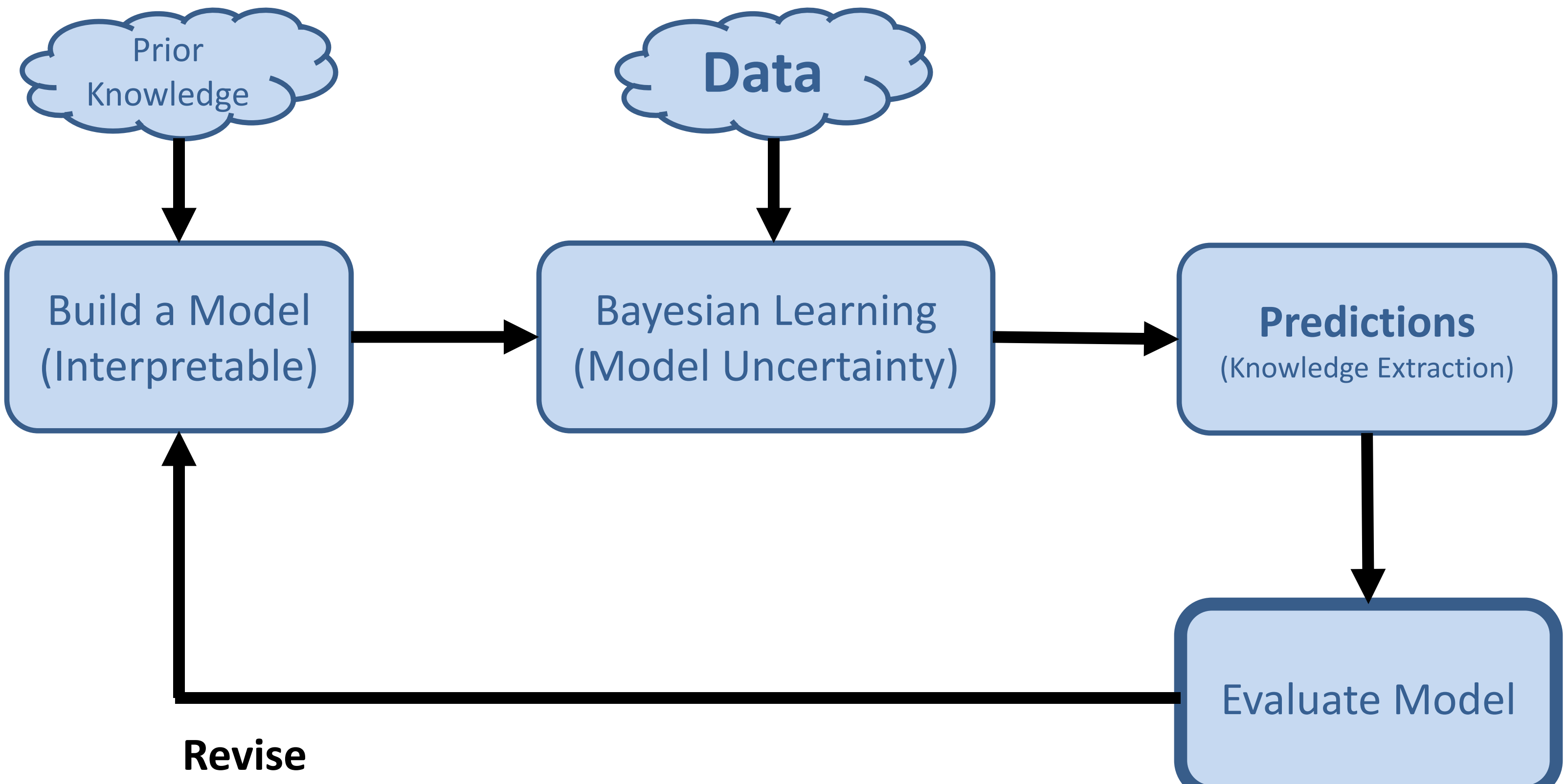



$$p(Fire = true | t1, t2, s1)$$

# Query the Model

Computing posterior probabilities given evidence

# MODEL-BASED MACHINE LEARNING

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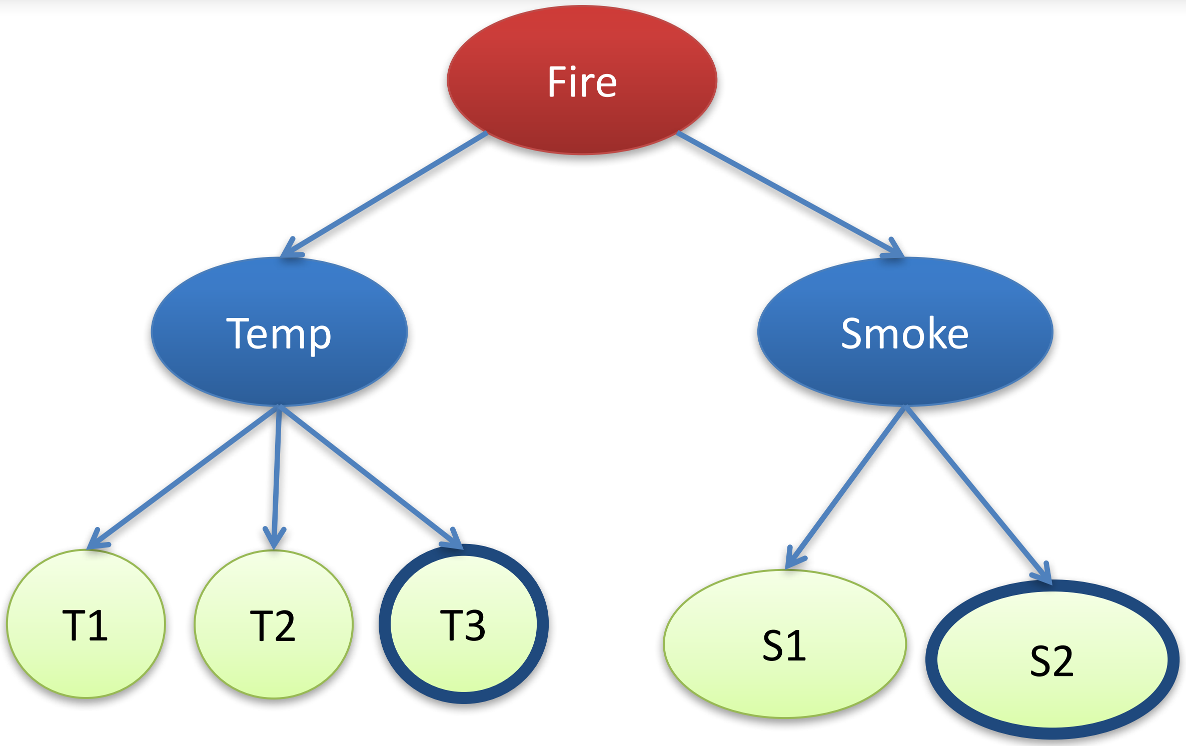
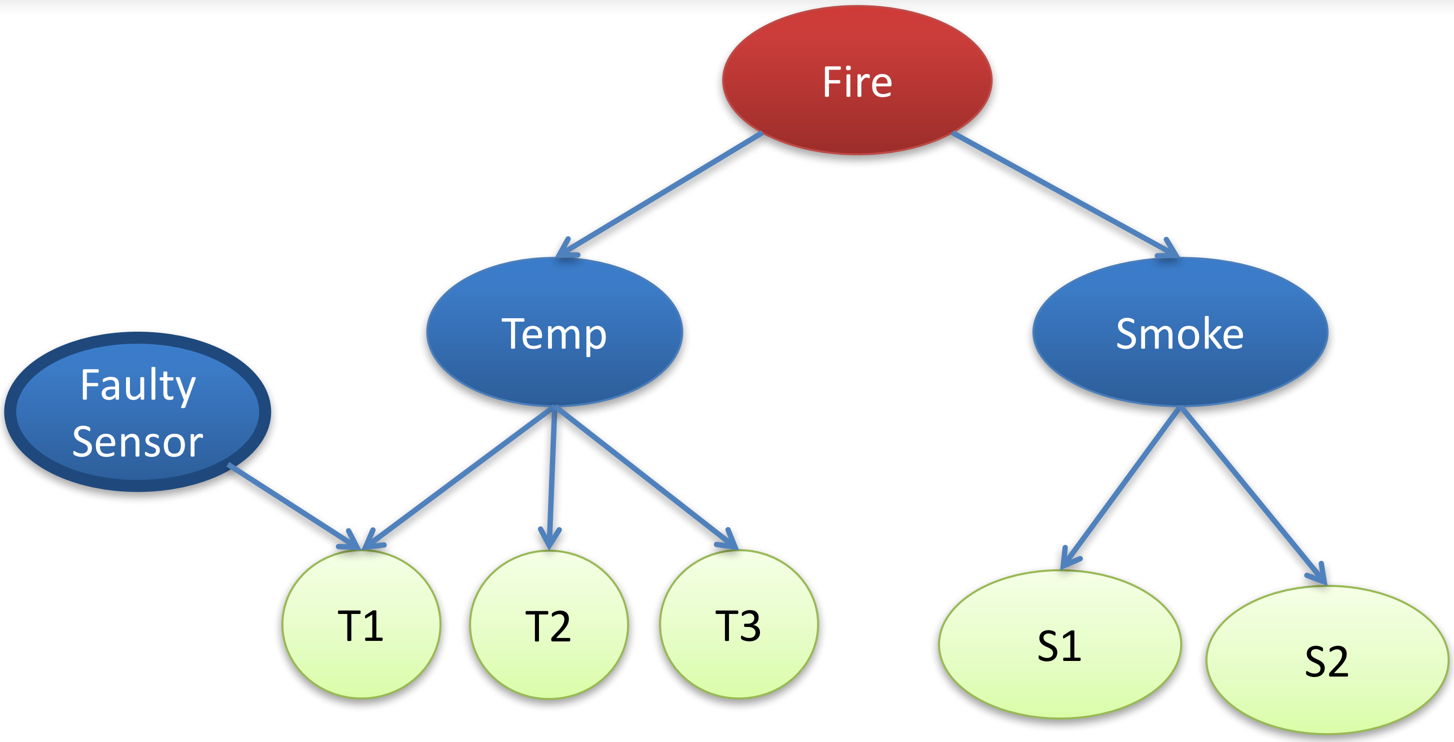


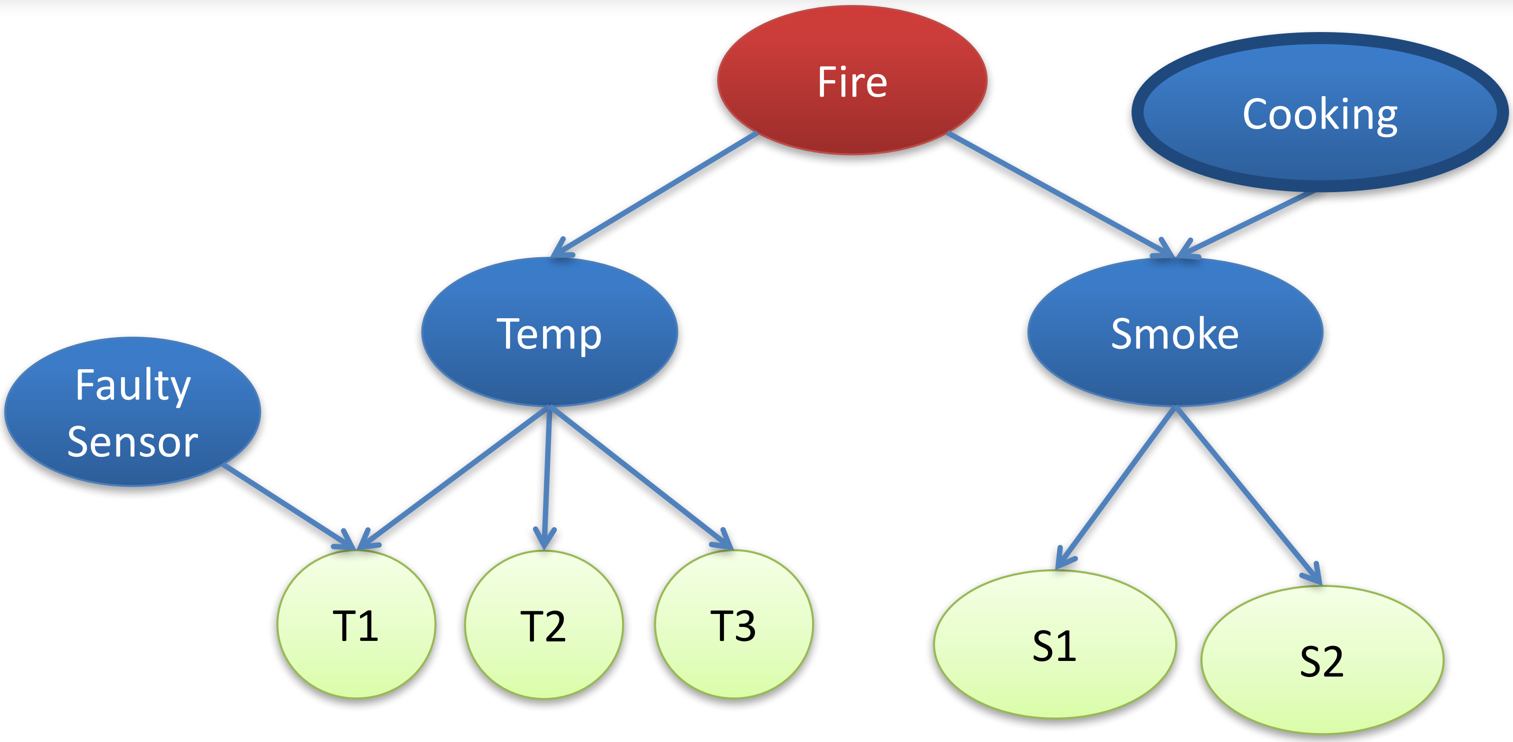

What if I have more sensors?

# Example of PGMs



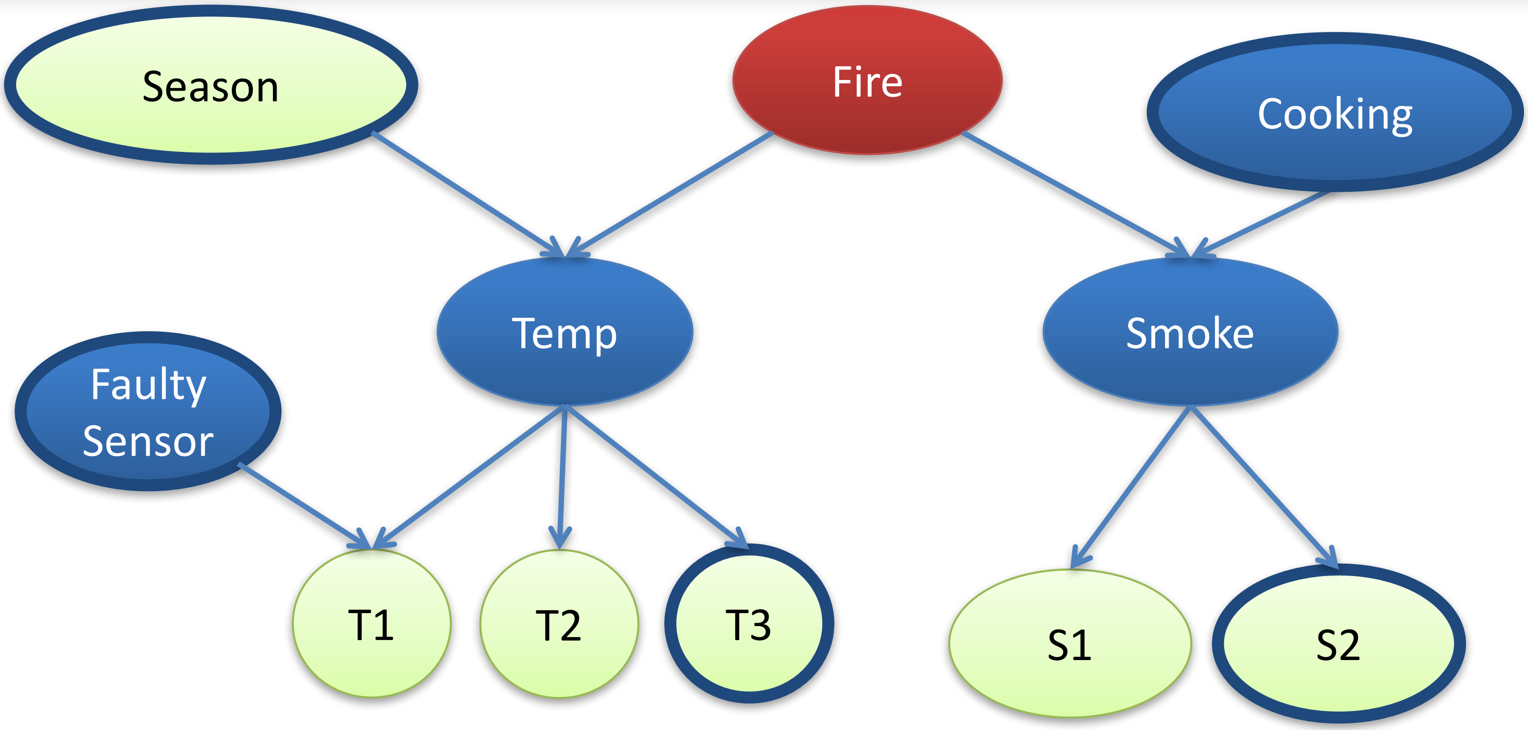

What if a sensor fails?

# Example of PGMs




What if the system is placed in a kitchen?

# Example of PGMs




What is normal indoor temperature changes through the season?

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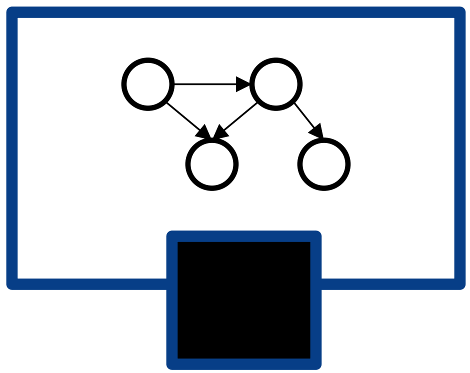
## Openbox Models

[Probabilistic Graphical Models]

**[Big] Data**

[+Prior Information]



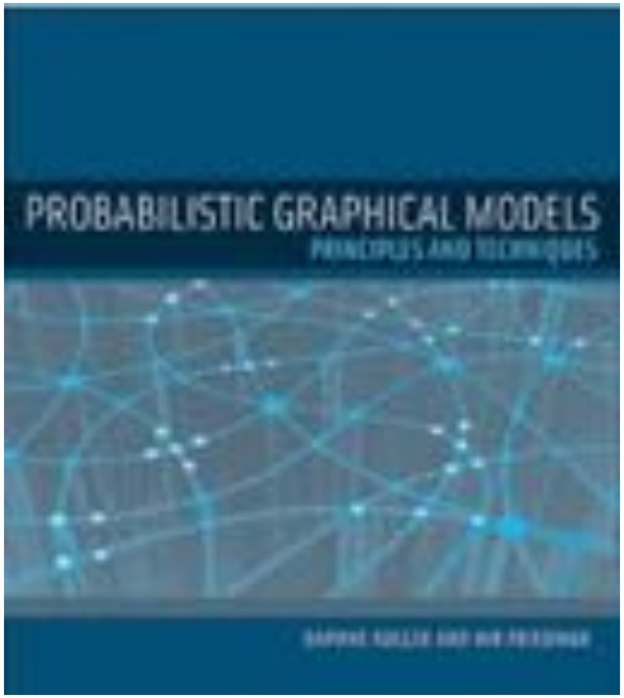
**Knowledge**

[+ Predictions]

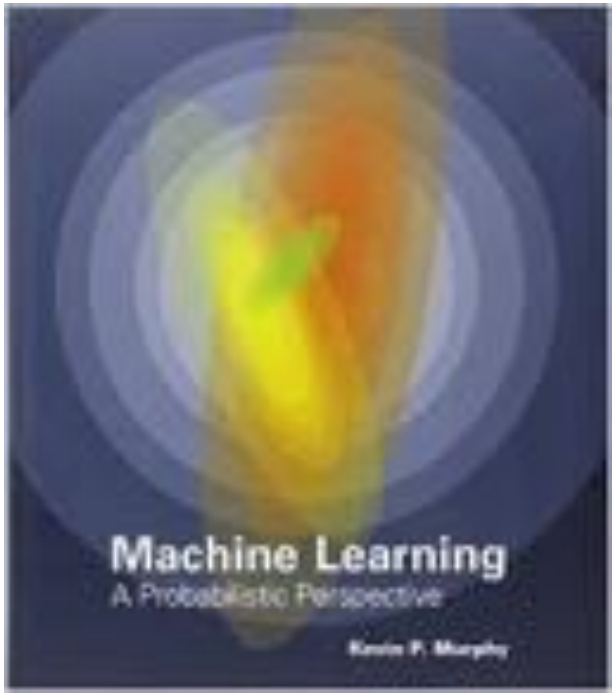
## [Scalable] Bayesian Inference Engine

(Powered by Variational Methods)

# AMIDST Approach




+




Probabilistic **Graphical Models**

Probabilistic Machine Learning

# Thanks for your attention

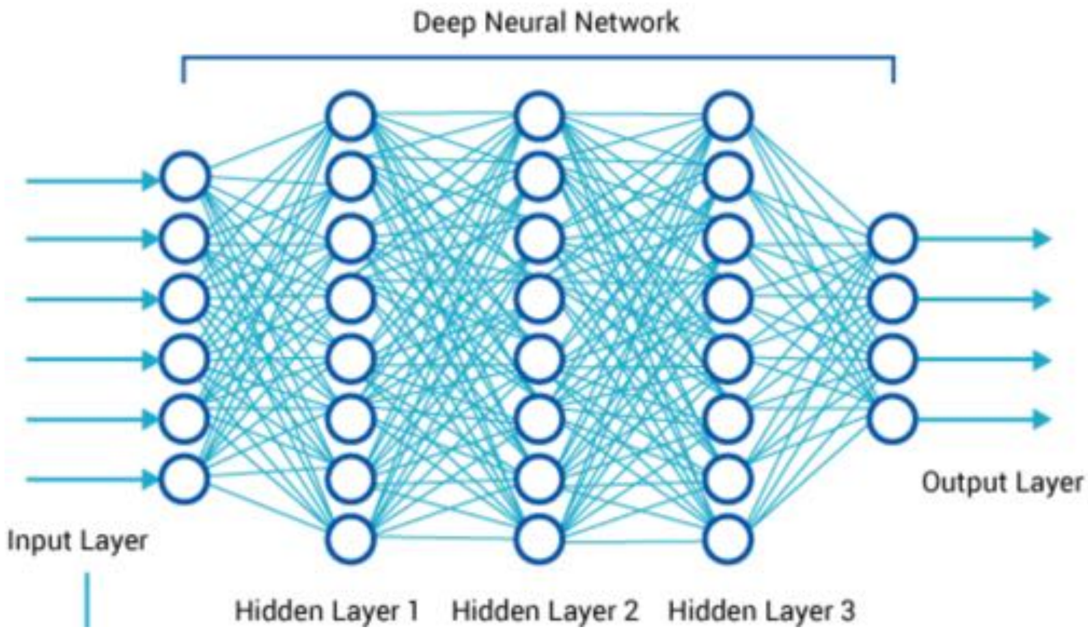
www www.amidsttoolbox.com

@ contact@amidsttoolbox.com

@AmidstToolbox

AMiDST TOOLBOX

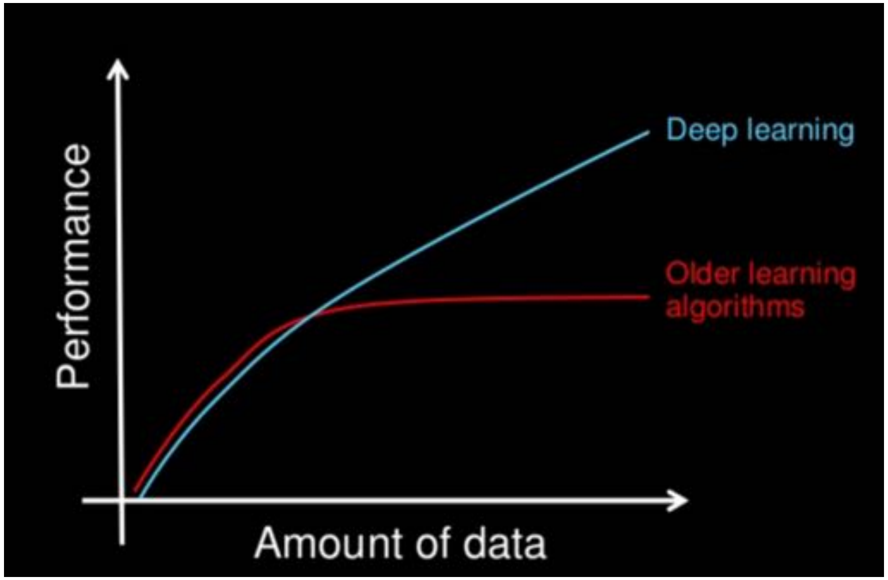
# WHAT ABOUT DEEP LEARNING?




**DNN are highly non-linear mappings**

# Deep Learning






$$f_\theta : X \to Y$$

$$\mathcal{D} = \{(x_1, y_1), \ldots, (x_n, y_n)\}$$

$$\theta^\star = \arg\min_\theta \sum_{i=1}^{n} \ell((x_i, y_i); \theta)$$

Andrew Ng: Artificial Intelligence is the New Electricity.
https://www.youtube.com/watch?v=21EiKfQYZXc&t=1206s

- Beyond supervised classification
  - **K-means clustering**'s loss function:

$$\sum_{i=1}^{n}\sum_{k=1}^{K} z_{ik}\|x_i - \mu_k\|^2$$

  - **Dimensionality Reduction**'s loss function:

$$\sum_{k=1}^{n}\left\|\left(\boldsymbol{\mu} + a_k \mathbf{e}\right) - \mathbf{x}_k\right\|^2$$

  - **Collaborative Filtering**'s loss function:

$$\sum_{(i,j):r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)})^2$$

Andrew Ng. Coursera. Machine Learning.
https://en.coursera.org/learn/machine-learning

# STANDARD APPROACH

## Blackbox Models

(kernel methods, deep learning, ensembles…)


## Loss Minimization

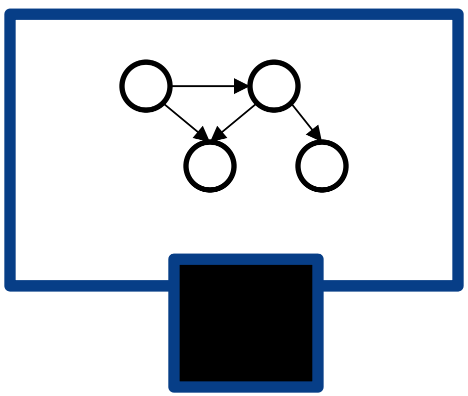
(Stochastic Gradient Descent)

## Openbox Models

[Probabilistic Graphical Models]

**Data**

[+Prior Information]



**Knowledge**

[+ Predictions]

## Black-Box Learning Engine

(Bayesian inference)