Me 375: Wildfire Science

ML Fundamentals

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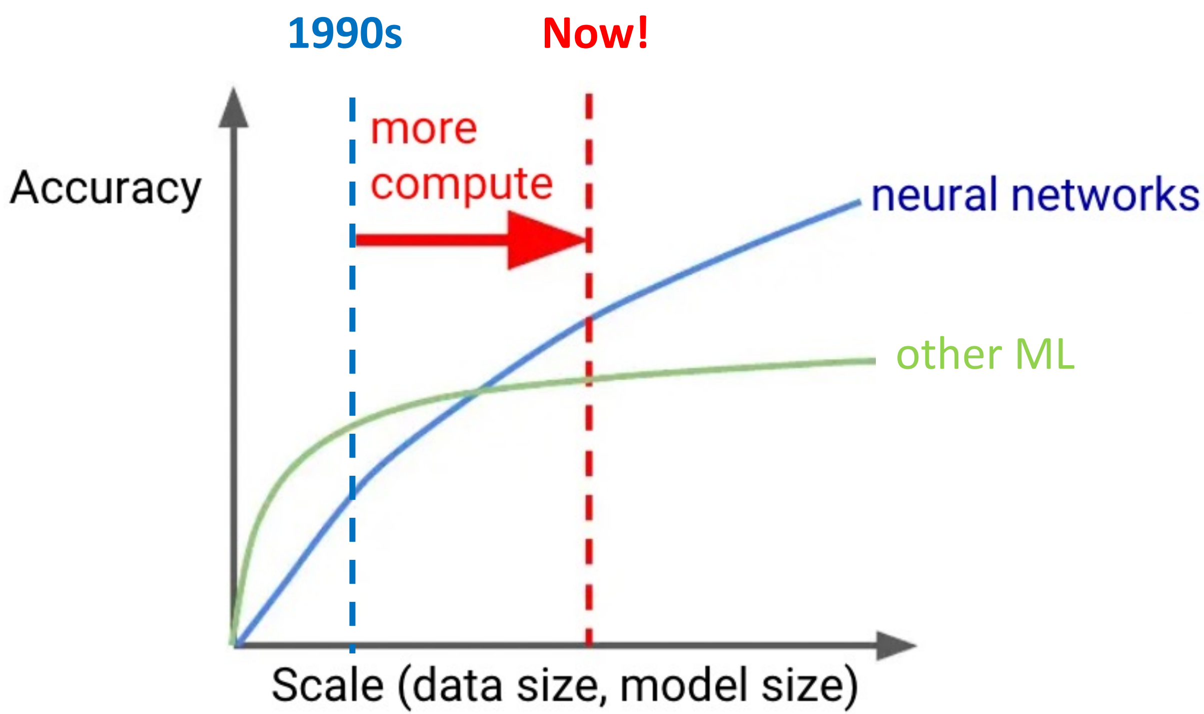
Mechanical Engineering

Agenda

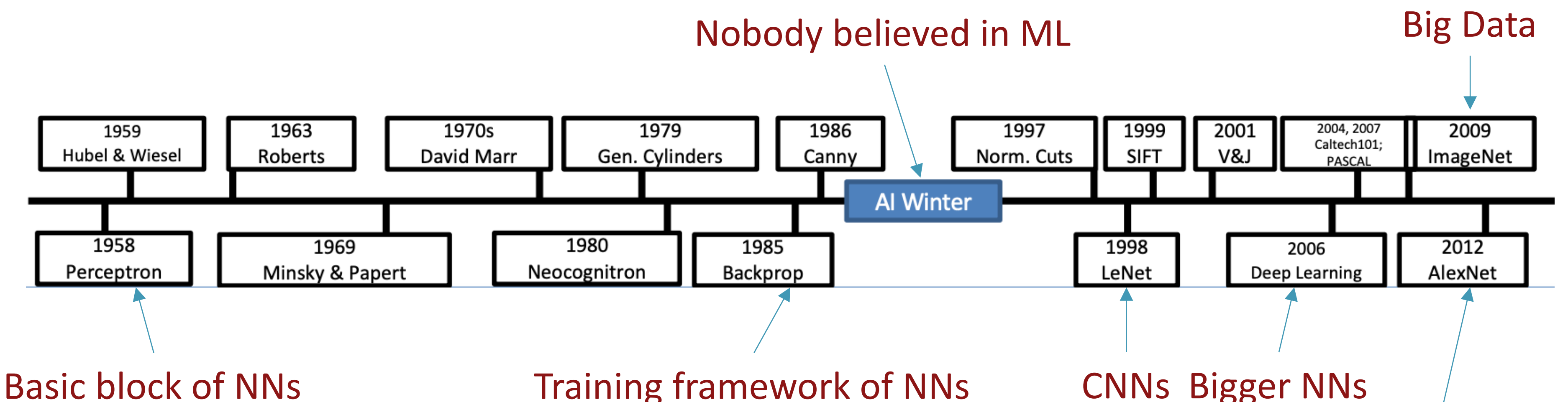
- Machine Learning
- Supervised Learning
- Logistic Regression
- Deep Learning
- ML in practice
    - Evaluation
    - Hyperparameter search
    - Train Test Split
    - Overfitting
- Classification and Regression Trees

Why is ML/Data science important (again)



Jeff Dean, Lecture for YCombinator AI (2017)

Timeline of ML



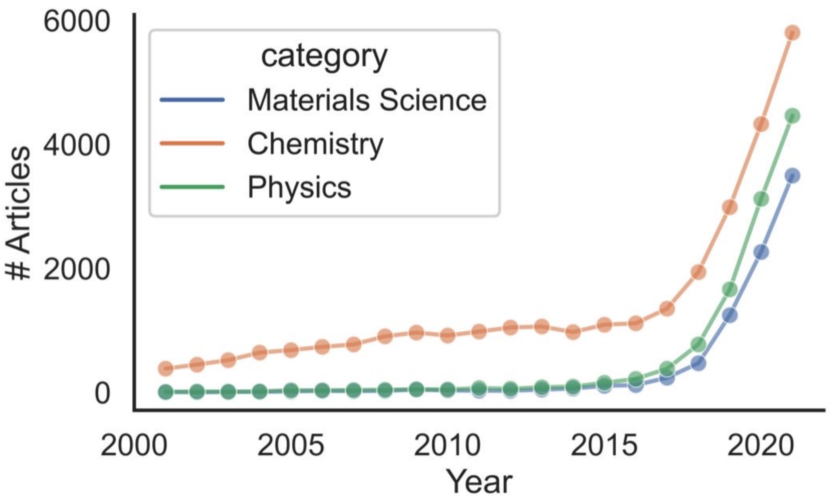
It took 27 years to believe in a good idea!
(Because of compute, data, etc.)

Never fear that your methods are too expensive/infeasible

L. Fei-Fei et. al., CS231N (2023)

AI/ML for Science

No. of ML for Science papers



One of the Biggest Problems in Biology Has Finally Been Solved

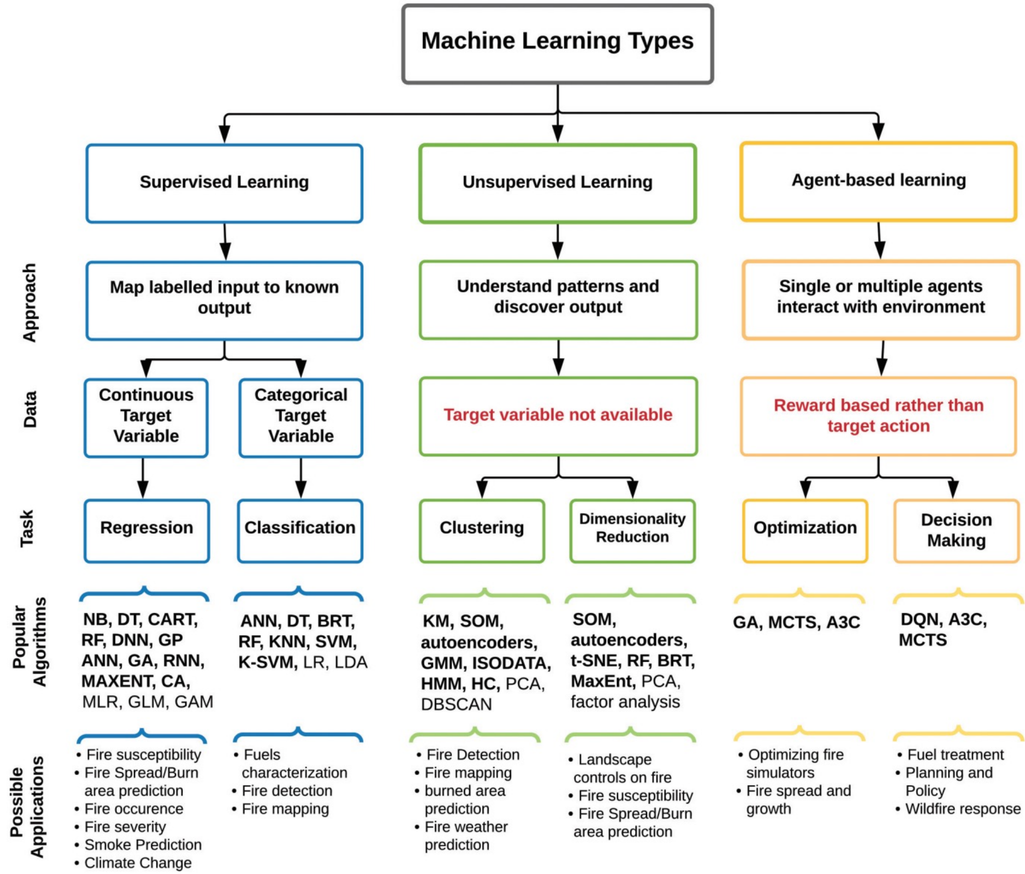
Google DeepMind CEO Demis Hassabis explains how its AlphaFold AI program predicted the 3-D structure of every known protein

DeepMind breaks 50-year math record using AI; new record falls a week later

AlphaTensor discovers better algorithms for matrix math, inspiring another improvement from afar.

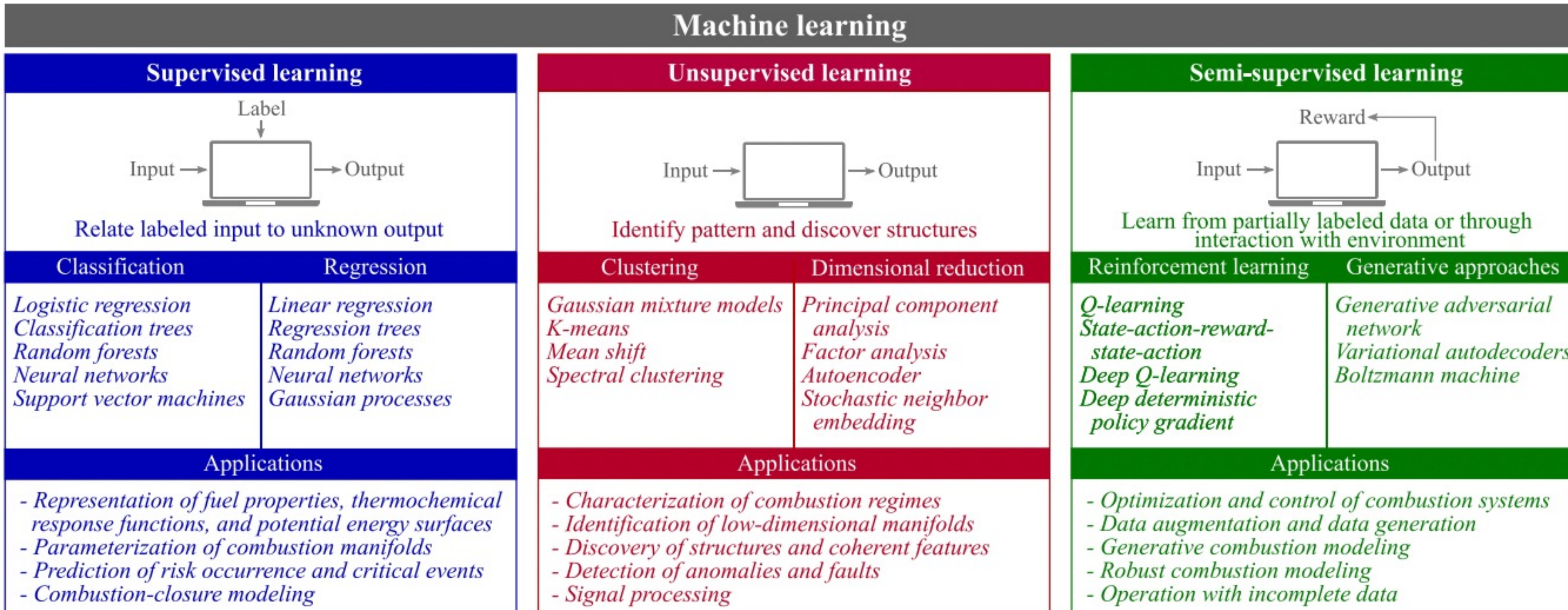
B. Blaizik, Twitter (2022)

Machine Learning for Wildfires



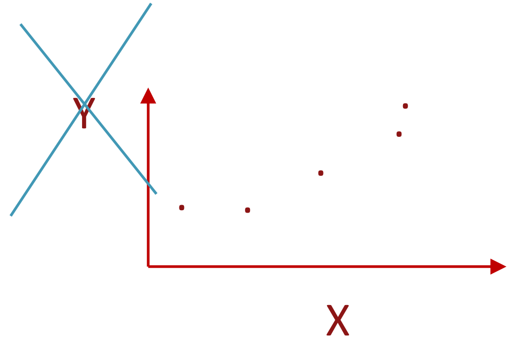
P. Jain et al. Env. Rev. (2020)

Alternatively: ML for Fundamental Combustion

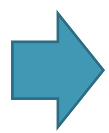


Ihme et al., Prog. Energy Combust. Sci. (2022)

Unsupervised learning

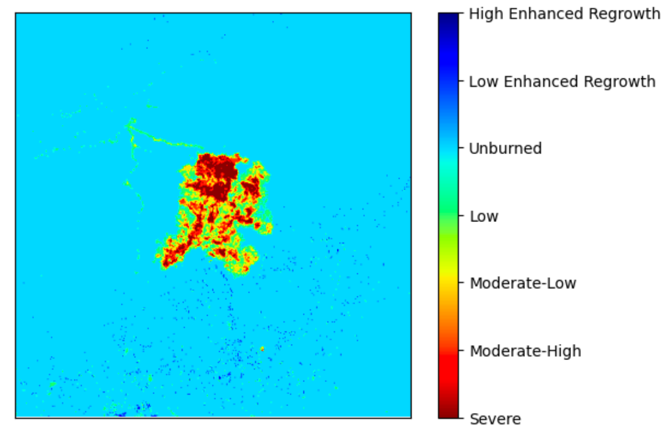


Example: Unprocessed satellite images



An Ideal Clustering Algorithm

Fire Severity Map



Reality: Not as powerful as supervised learning

Supervised learning - Predictions

Classification

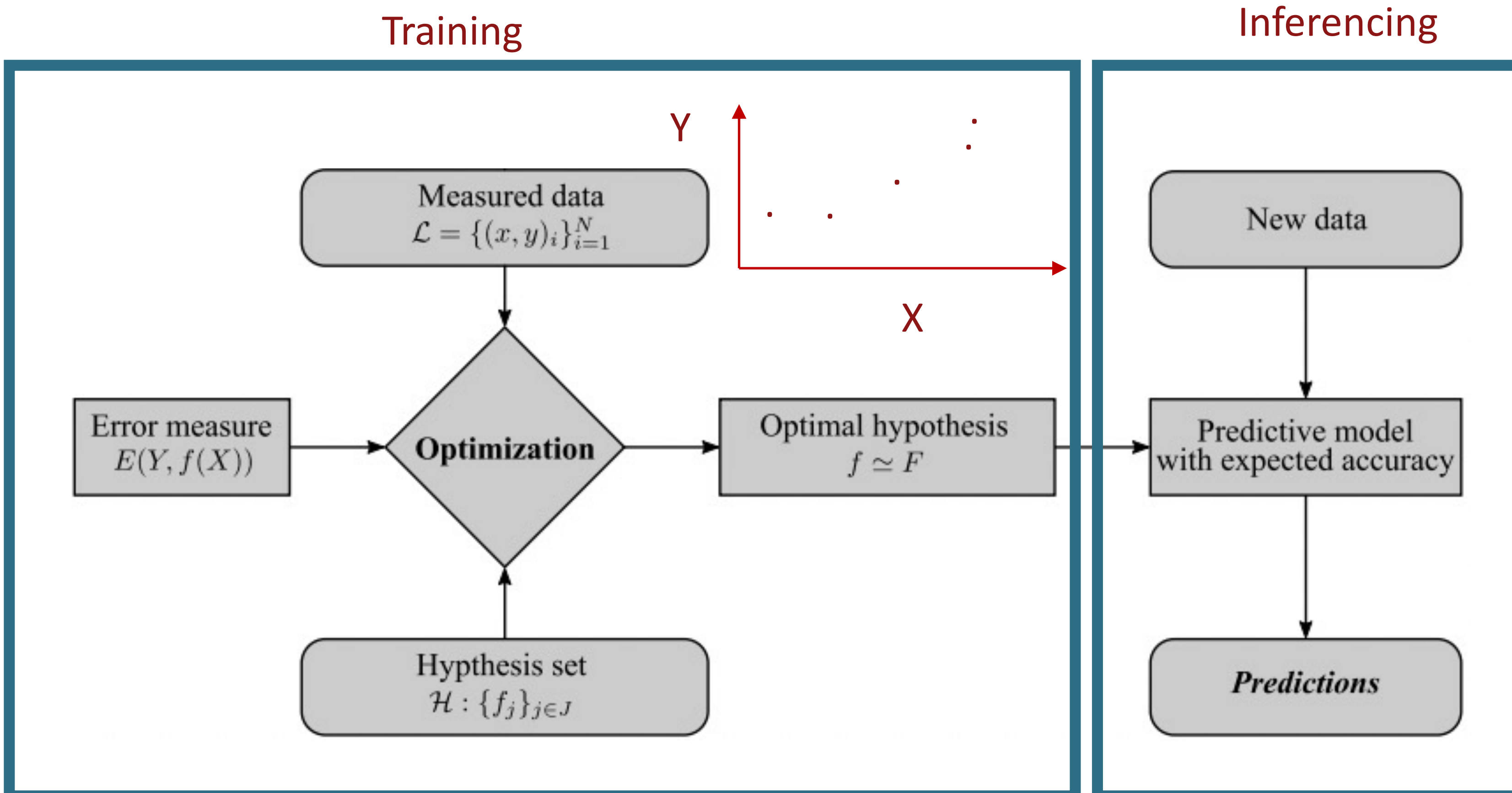
Which leaf is burning?
Ans:
Leaf 1, leaf 2, leaf 3 …

Regression

How hot is my tree?
Ans:
Leaf 1 is 735.222,
Leaf 2 is 314.159…

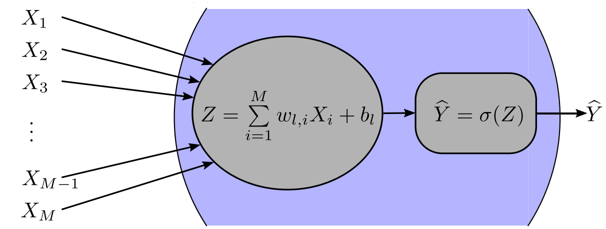
Ihme et al., Prog. Energy Combust. Sci. (2022)

How is this done?



Logistic Regression Classifiers

Simplest Classifiers



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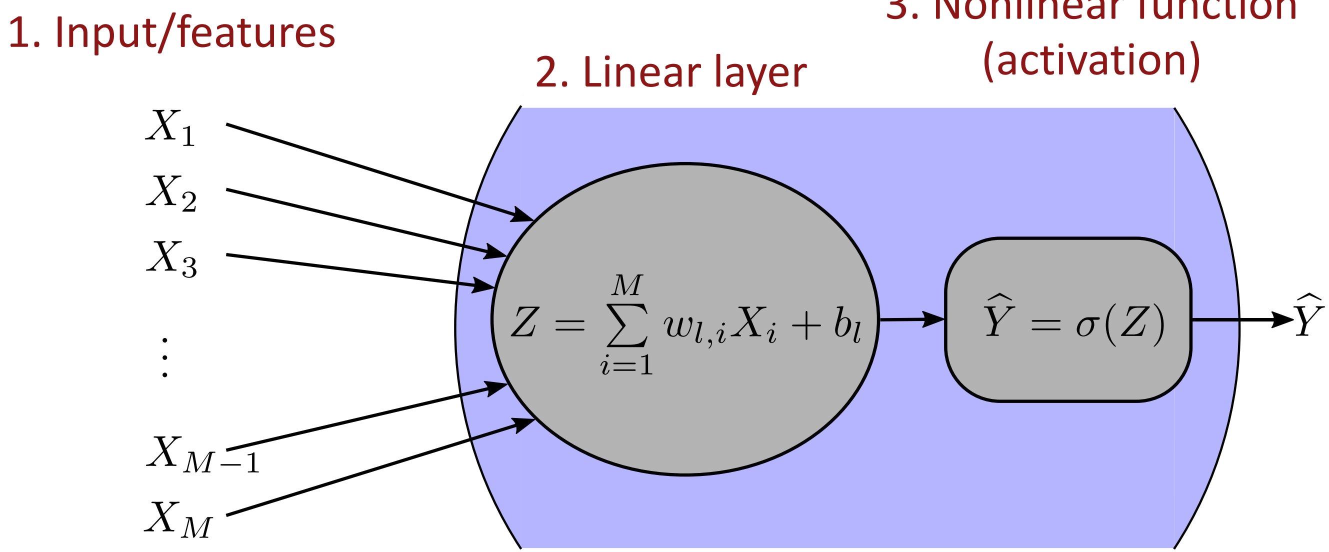
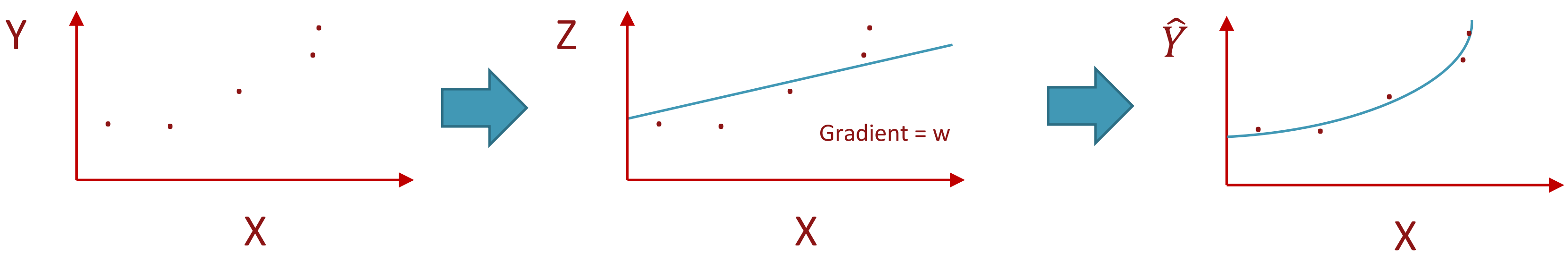
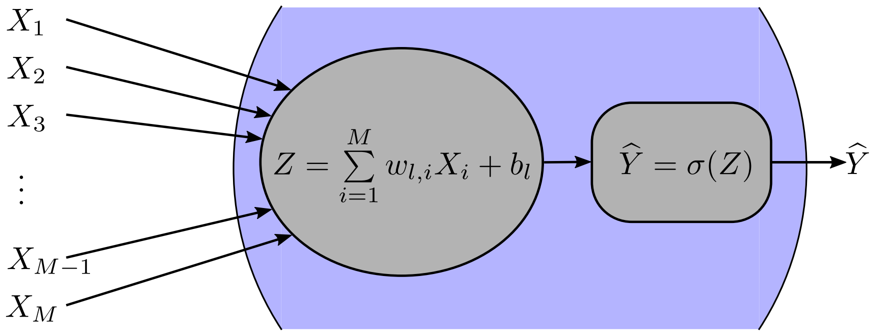
Logistic regression



Output:
Probability of a sample belonging to a class, e.g. P(leaf burning)

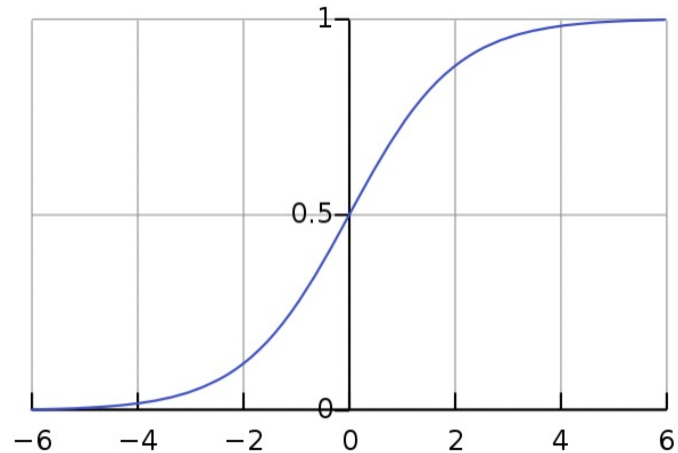


Logistic regression - classification



- Output $\hat{Y}$ is the Probability, e.g. P(leaf burning).
- $\boldsymbol{\sigma}$ is a sigmoid function

$$S(x) = \frac{1}{1+e^{-x}} = \frac{e^x}{e^x+1} = 1 - S(-x).$$



- Does 2 things:
  - Normalizes your prediction between 0 and 1 (Like probability)
  - Pushes small values to 0, big values to 1

Training logistic regression - Likelihood

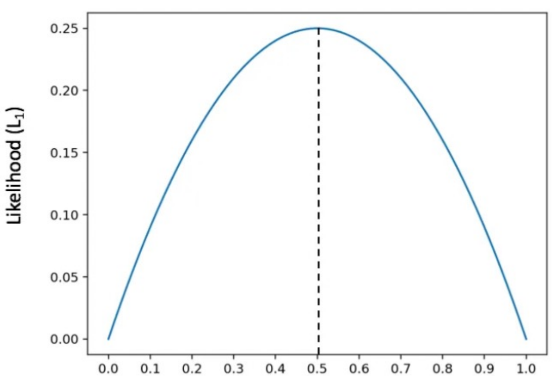
We want to maximize the likelihood of of an event.

Likelihood is the product of all possible probability functions

For a 2 coin toss

Outcome = [H,T]

$$L_1 = P(H)P(T)$$
$$L_1 = Y(1 - Y)$$

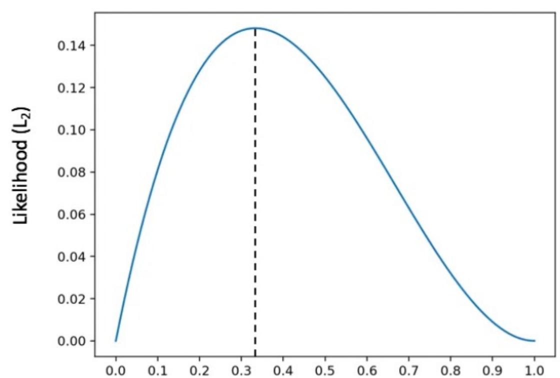


Y = P(H|Outcome = [H,T])

For a 3 coin toss

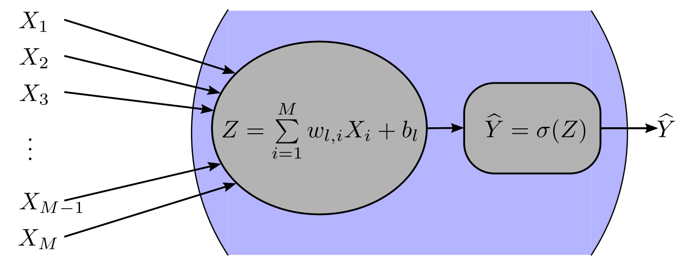
Outcome = [H,T,,T]

$$L_2 = P(H)P(T)P(T)$$
$$L_2 = Y(1 - Y)(1 - Y)$$



Y = P(H|Outcome = [H,T,T])

Max L -> Correct probability

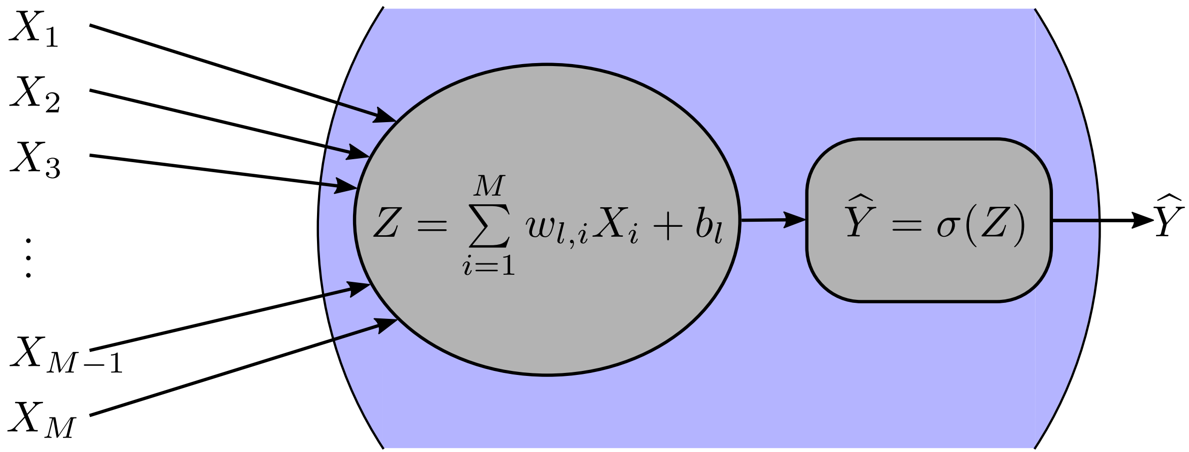


Maximize this function

$$L(\hat{Y}(w)) = \prod_{i=1}^{n} \hat{Y}^{class}(1 - \hat{Y})^{1-class}$$

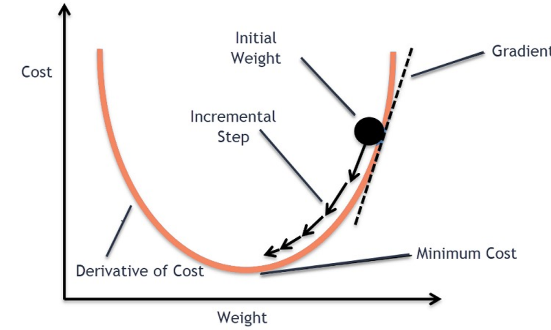
L.F. Caramillo-Guererro, Medium (2019)

Training logistic regression

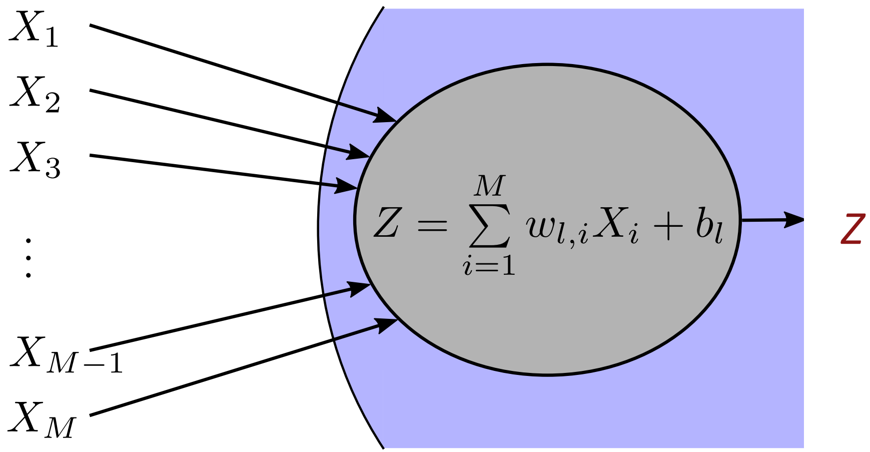


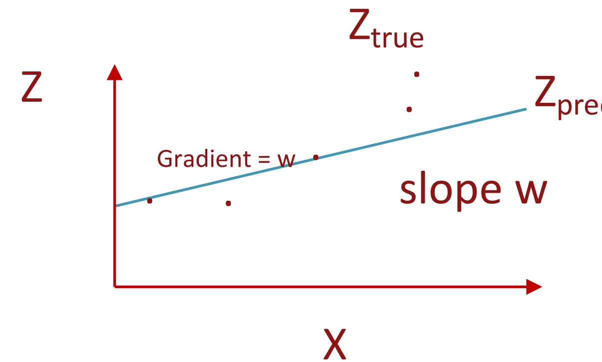
Find w that maximizes L($\hat{Y}(w)$)

- We do this via Optimization Algorithms
- The most popular is Gradient Descent-based
    - Take negative log of likelihood – minimize cross entropy
- You can do this via model.fit in most python ML packages



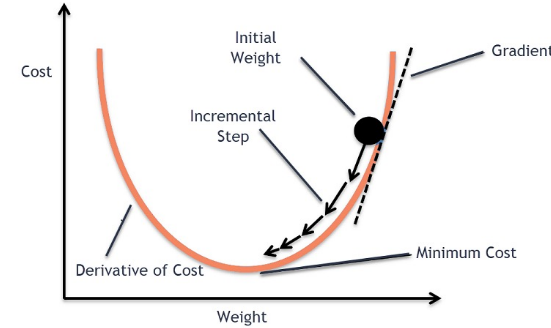
Similar to linear regression





Find w that minimizes error MSE(Z_{true},$Z_{predicted}$) or MAE

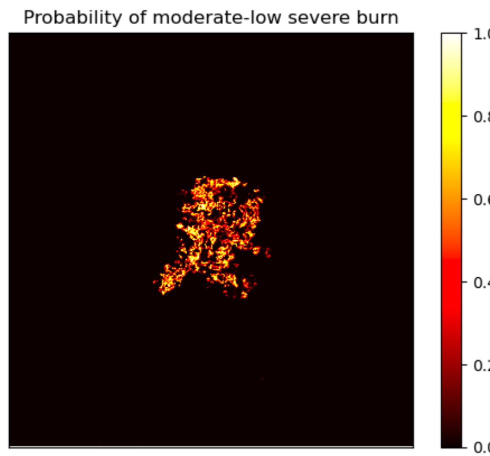
- We do this via Optimization Algorithms
- The most popular is Gradient Descent-based
- You can do this via model.fit in most python ML packages



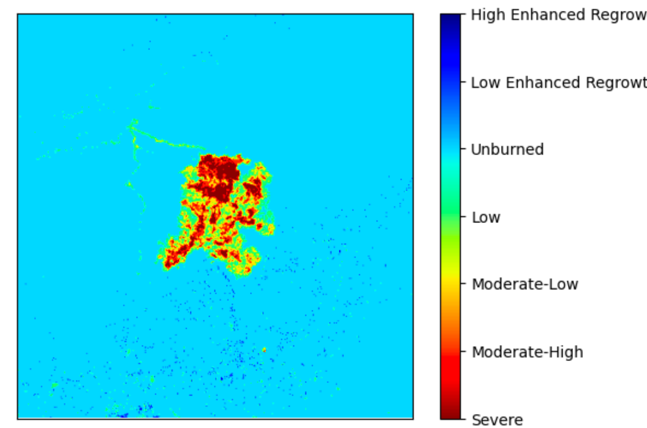
Example of Predicting Fire Severity

ML Input X

ML Output $\hat{Y}$

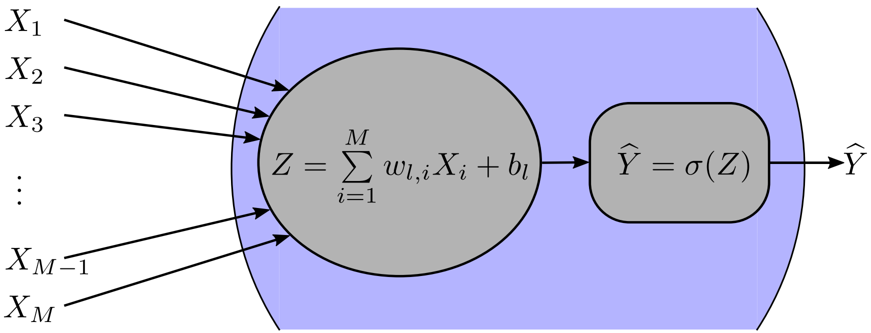


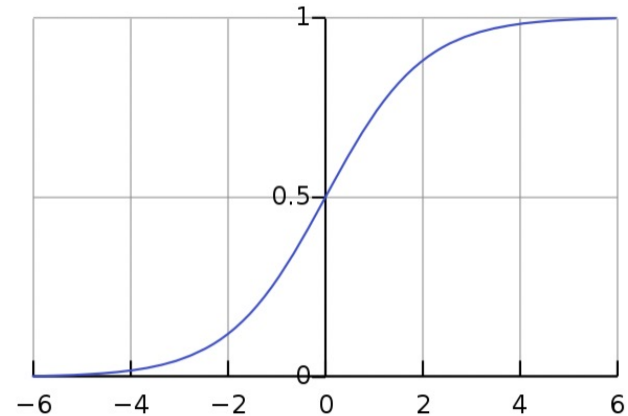
Fire Severity Map



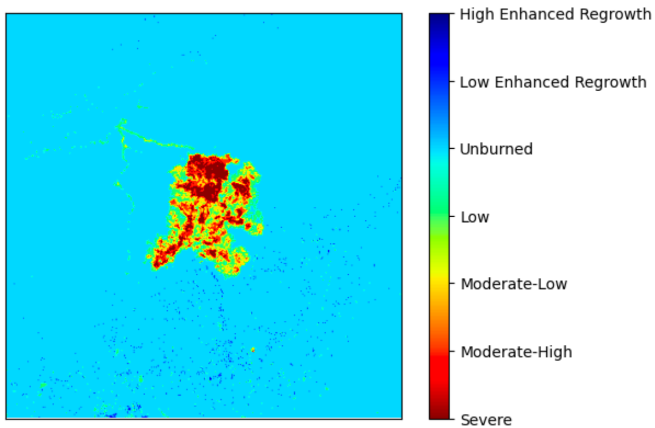
What's Missing?

Multiclass logistic regression



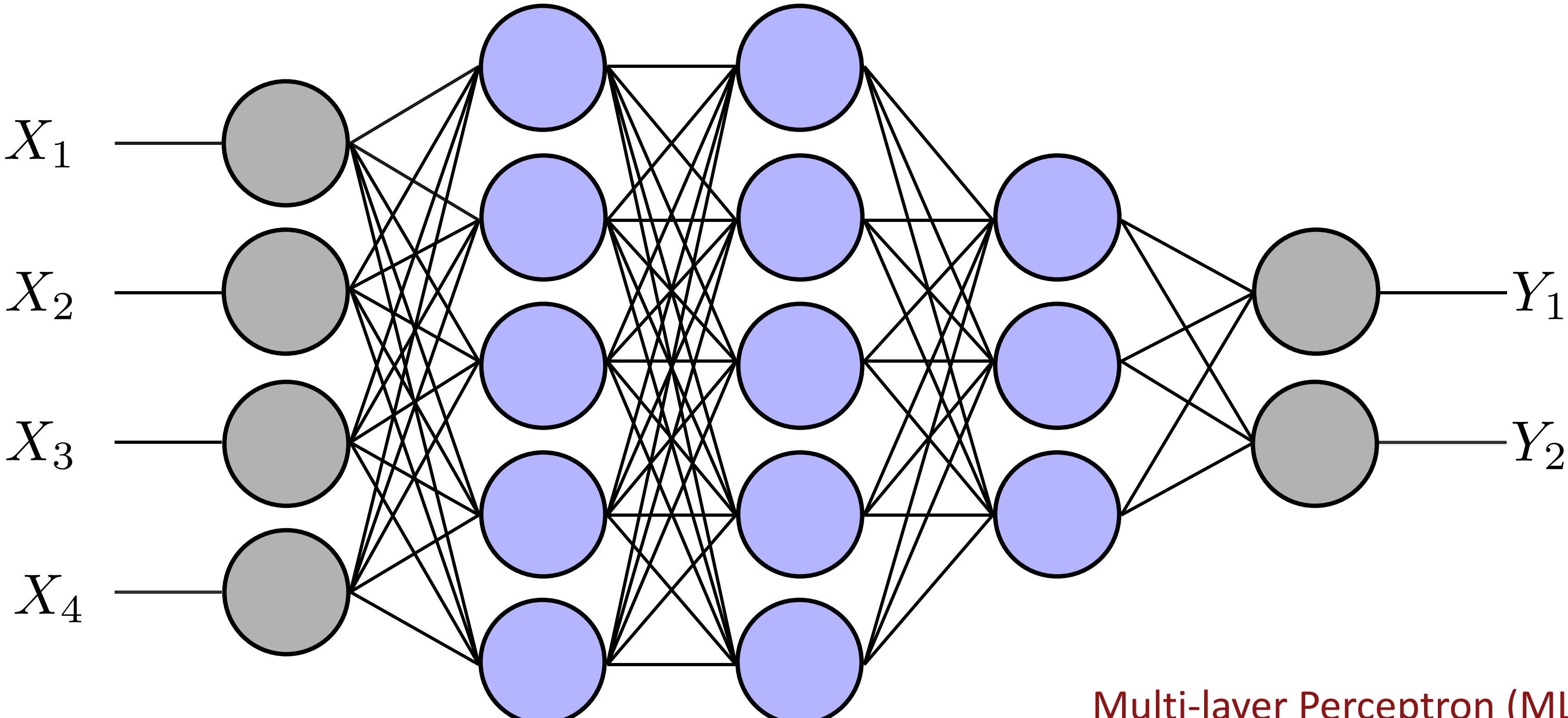


- So far we've only discussed binary classification.
- How to do multiclass classification?



Class	Labels						
High Regrowth	1	0	0	0	0	0	0
Low Regrowth	0	1	0	0	0	0	0
Unburned	0	0	1	0	0	0	0
Low	0	0	0	1	0	0	0
Moderate-Low	0	0	0	0	1	0	0
Moderate-High	0	0	0	0	0	1	0
Severe	0	0	0	0	0	0	1

Neural Networks – A bunch of connected logistic regression nodes

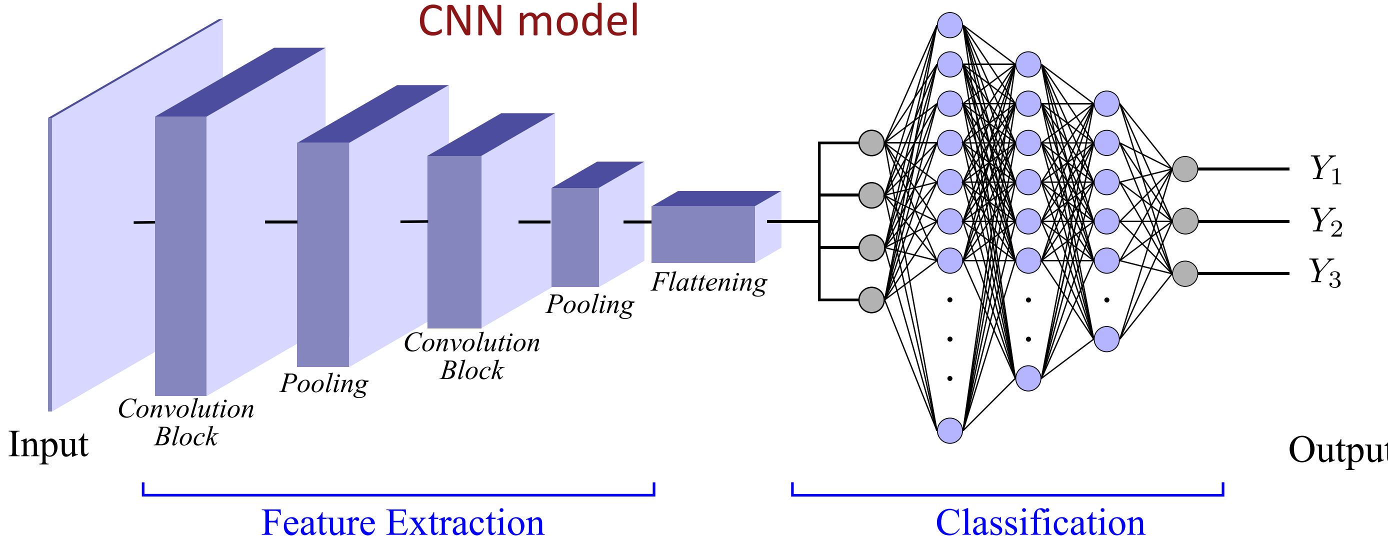


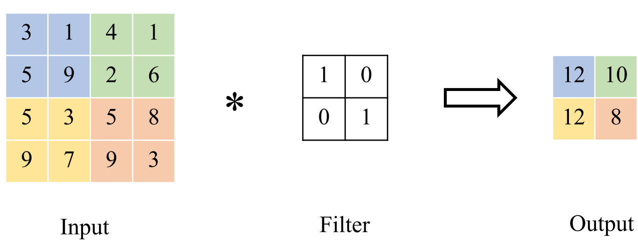
Multi-layer Perceptron (MLP)

Ihme et al., Prog. Energy Combust. Sci. (2022)

Deep learning

CNN model





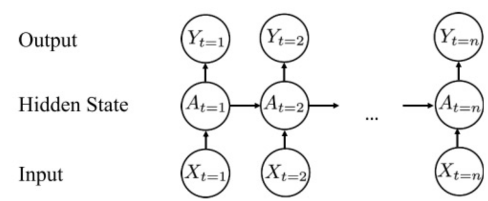


Fig. 16. Schematic of a many-to-many RNN.

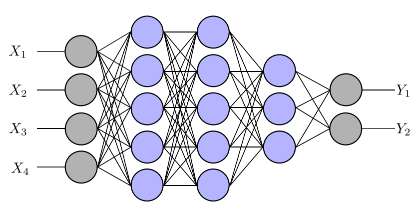
RNN model

Transformer architectures

ChatGPT

GPT3

175B parameters
$5M to train



76 param model

Attention Is All You Need

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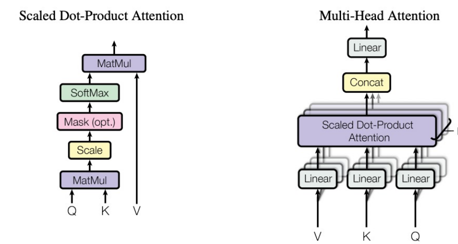


Table 2: The Transformer achieves better BLEU scores than previous state-of-the-art models on the English-to-German and English-to-French newstest2014 tests at a fraction of the training cost.

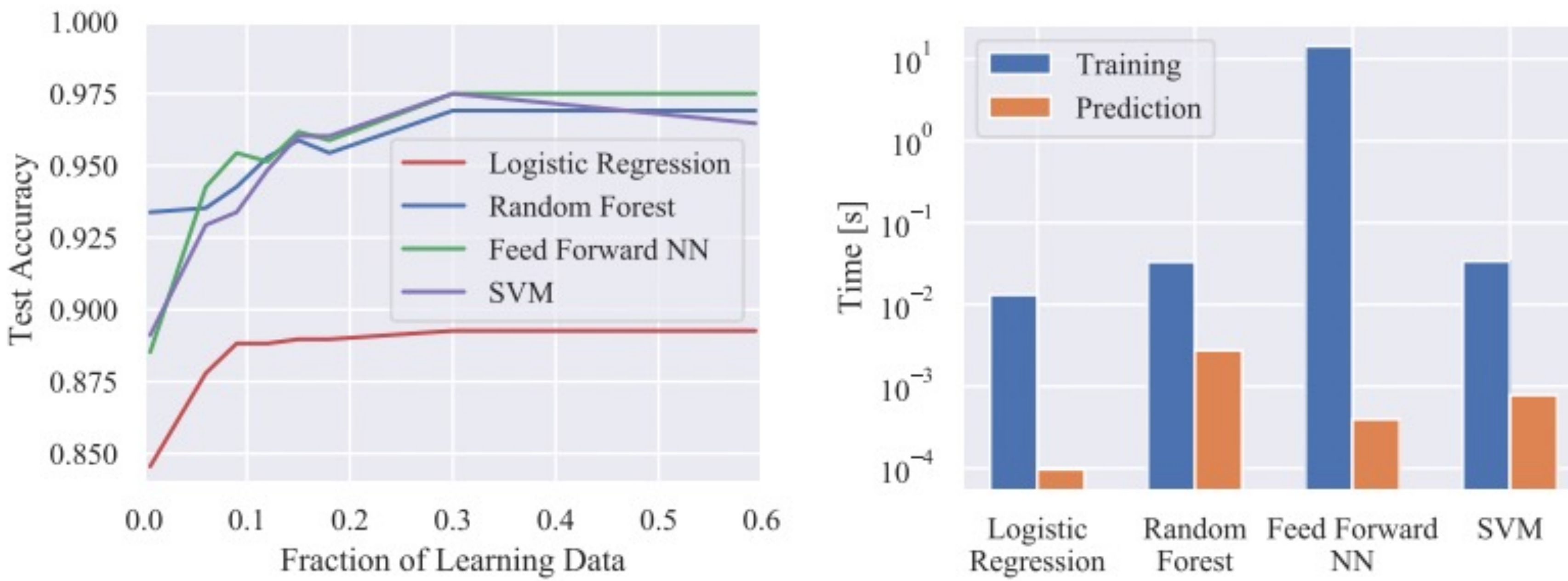
Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [18]	23.75			
Deep-Att + PosUnk [39]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [38]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [9]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [32]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [39]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [38]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [9]	26.36	**41.29**	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	$\mathbf{3.3 \cdot 10^{18}}$	
Transformer (big)	**28.4**	**41.8**	$2.3 \cdot 10^{19}$	

Algorithms

Classification	Regression
Logistic regression	*Linear regression*
Classification trees	*Regression trees*
Random forests	*Random forests*
Neural networks	*Neural networks*
Support vector machines	*Gaussian processes*

How do I choose the right model?

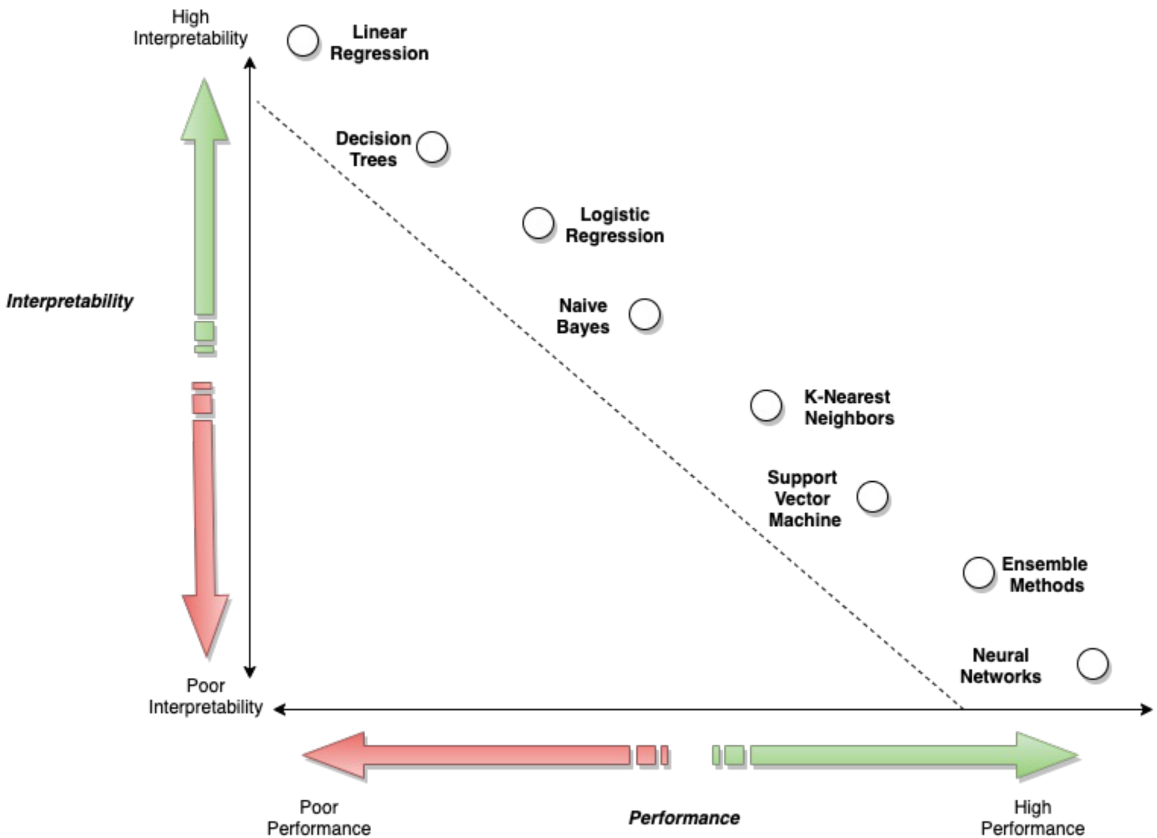
Typical trends in ML models



(a) Accuracy

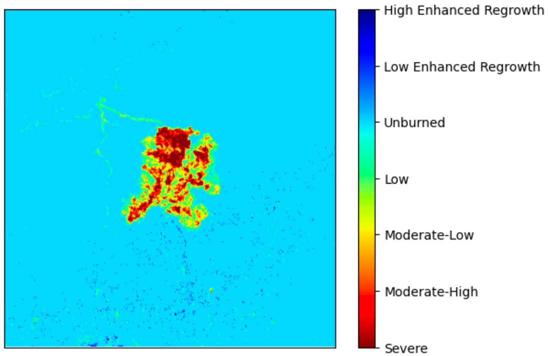
(b) Cost

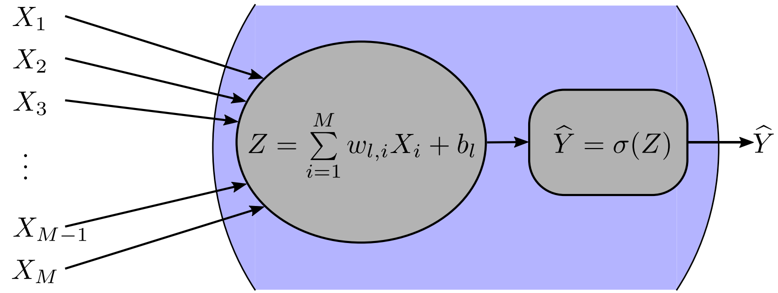
Interpretability

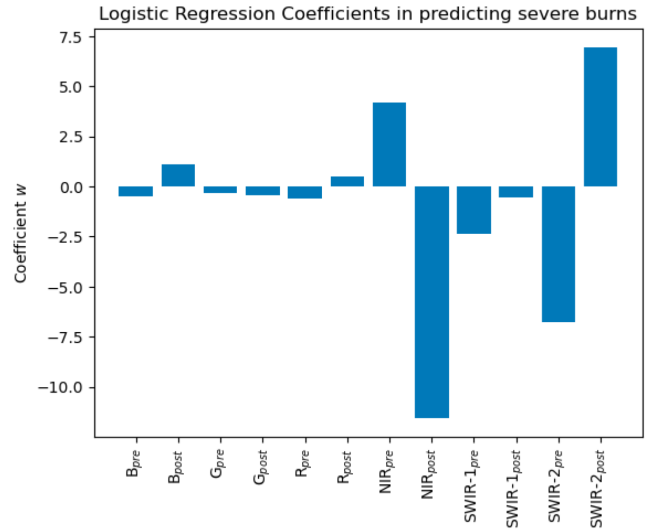


Amazon White Paper (2023)

Logistic regression Interpretability



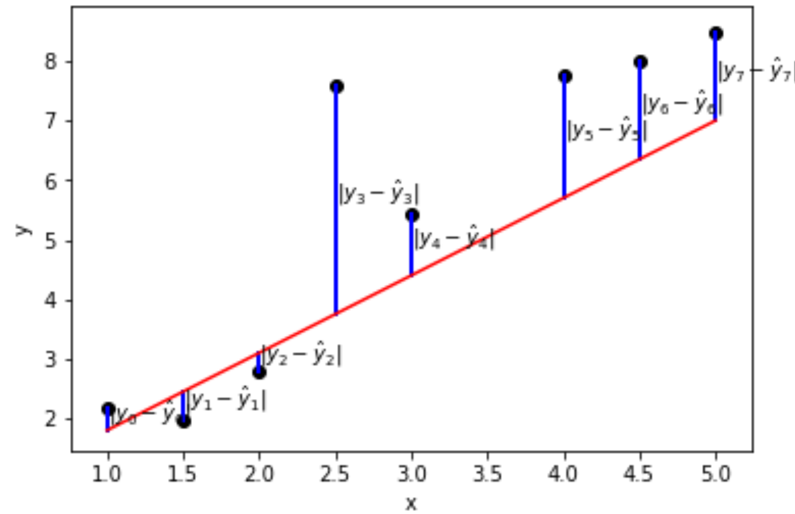




ML in Practice

Evaluation

- Regression
  - MAE
  - RMSE
- Classification
  - Accuracy
  - Precision
  - Recall
  - F1-Score



$$MAE = \frac{1}{n}\sum_{j=1}^{n} |y_i - \hat{y}_i|$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_i - \hat{y}_i)^2}$$

Gives more weight to outliers

Classification Metrics

		Predicted	
		Negative	**Positive**
Actual	**Negative**	True Negative	False Positive
	Positive	False Negative	True Positive

$$\text{Accuracy} = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative}$$

Only gives info on True Predictions, not on mistakes

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Lets you know when you have False Positives. E.g. Bank Fraud

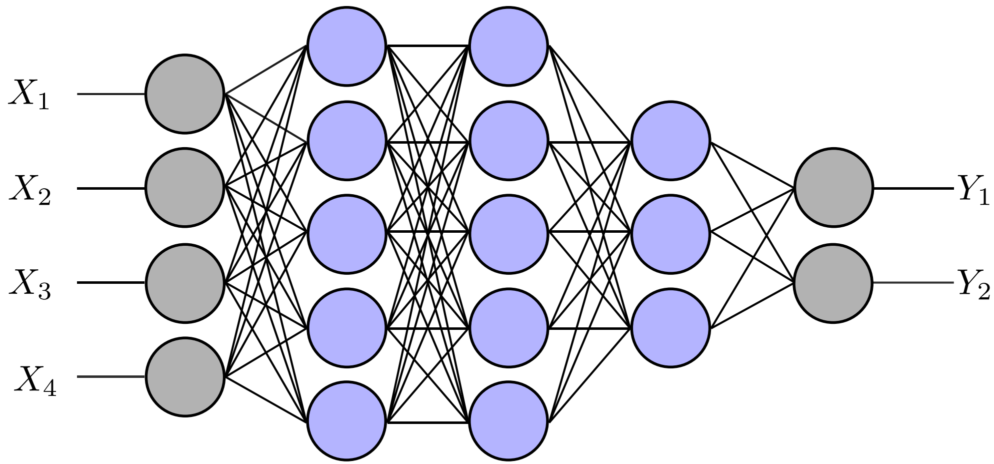
$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

Lets you know when you have False Negatives. E.g. COVID

$$\text{F1} = 2 \text{ x } \frac{Precision * Recall}{Precision + Recall}$$

Gives both FP and FN E.g. Search applications

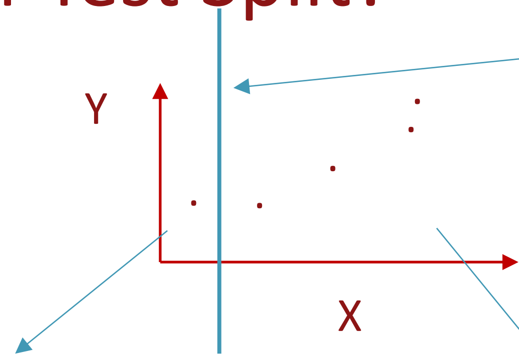
Hyperparameter search



How many neurons in each layer?
How many layers?
What optimization scheme?
How much data?
What forward operation?
What non-linearity?
NN or other method?

1. Intuition/Domain Knowledge
2. Exhaustive Search (Expensive!)
3. Random Search (Not efficient)
4. Bayesian Optimization (Gaussian Assumptions)
5. Reinforcement Learning
6. AutoML
7. …

Why do a Train-Test Split?



Partition via random selection in an 80:20 or 90:10 fashion.

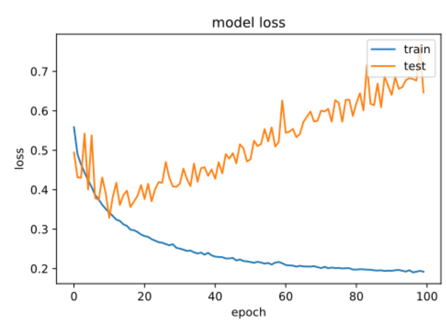
Test with this

Train with this

Why? - > Can Diagnose Overfitting

Loss is your objective function

- Likelihood
- Error between points



This can happen if your hyperparameter search arrives at a model that that only suits your train data

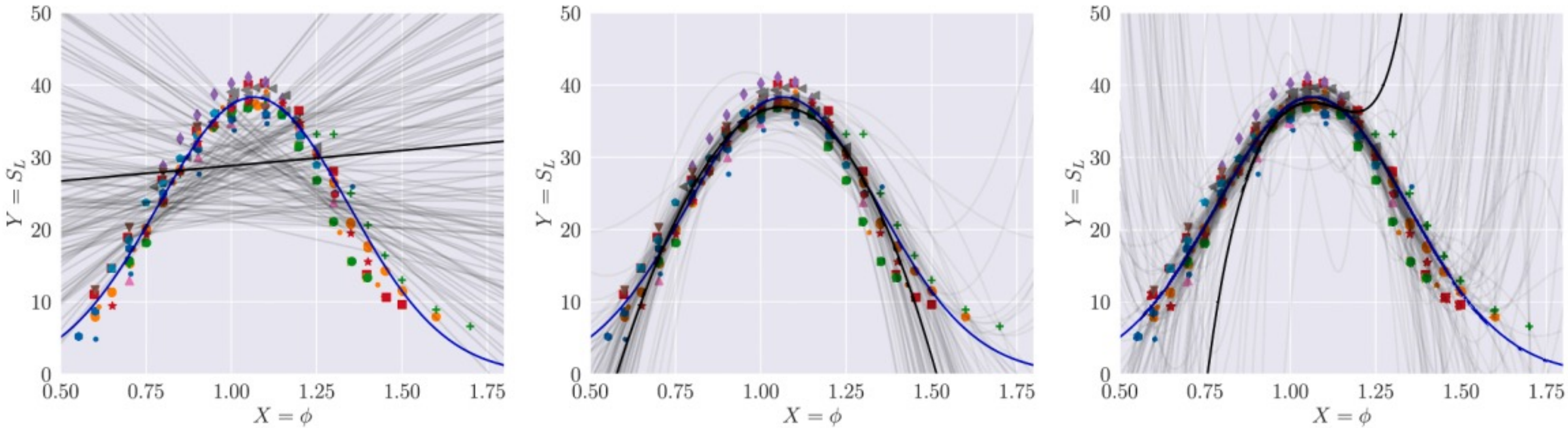
Why does overfitting occur?

- We train 100 linear regression models of different complexity
- More complex models (more layers, etc) can arrive at high bias.

Underfit
High variance

Decent fit

Overfit
High-bias



(a) 1[st] order regression.

(b) 3[rd] order regression.

(c) 5[th] order regression.

Better split: Train-test-validation split

- Train-test split let's you **diagnose overfitting!**
  - Doesn't actually do anything to stop this
- Train-val-test split can help alleviate overfitting
  - Hyper-parameter search on a validation set that is different from train and test set
- Partition via random selection in an 80:10:10 or 90:5:5 fashion.

Overfitting can happen if your hyperparameter search arrives at a model that that only suits your train data

Other ways to deal with overfitting

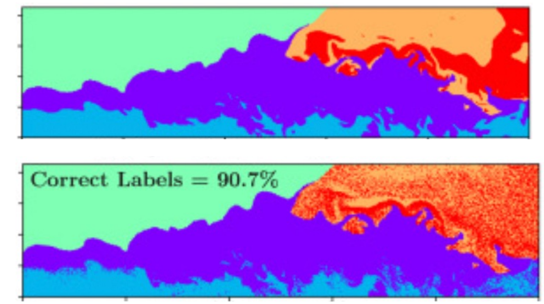
- Regularization
- Data augmentation
- Dropout
- Batch Normalization

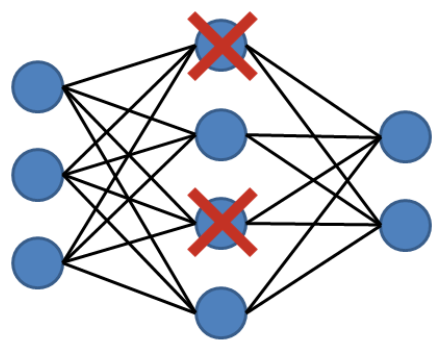
L1 Regularization

$$\text{Cost} = \sum_{i=0}^{N}(y_i - \sum_{j=0}^{M} x_{ij}W_j)^2 + \lambda \sum_{j=0}^{M} |W_j|$$

L2 Regularization

$$\text{Cost} = \underbrace{\sum_{i=0}^{N}(y_i - \sum_{j=0}^{M} x_{ij}W_j)^2}_{\text{Loss function}} + \underbrace{\lambda \sum_{j=0}^{M} W_j^2}_{\text{Regularization Term}}$$





Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

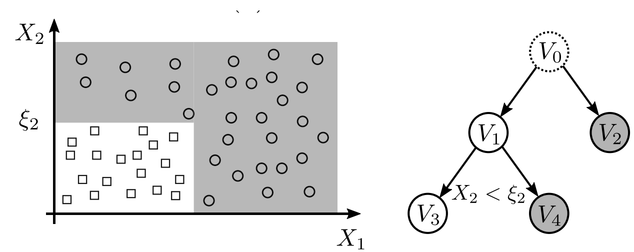
$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma\widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Classification and Regression Trees (CARTs)

An Interpretable Staple for Tabular Data



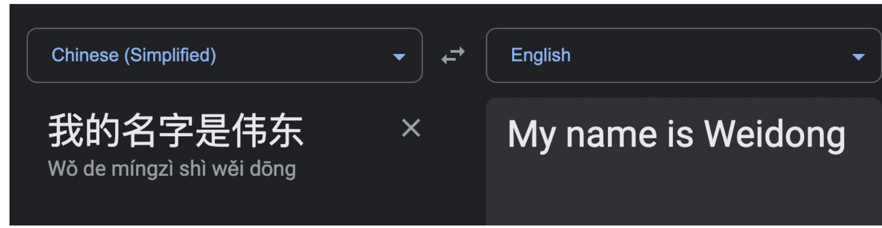
FX Lab Stanford University
Mechanical Engineering

Popular Data types

Images/Spatial (N-D)

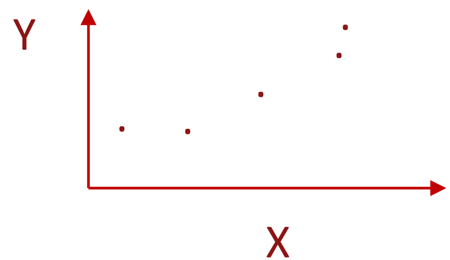
CNNs, Vision Transformers

Language/Sequential (1D)



RNNs, Transformers, LSTMs

Tabular Data (0D)



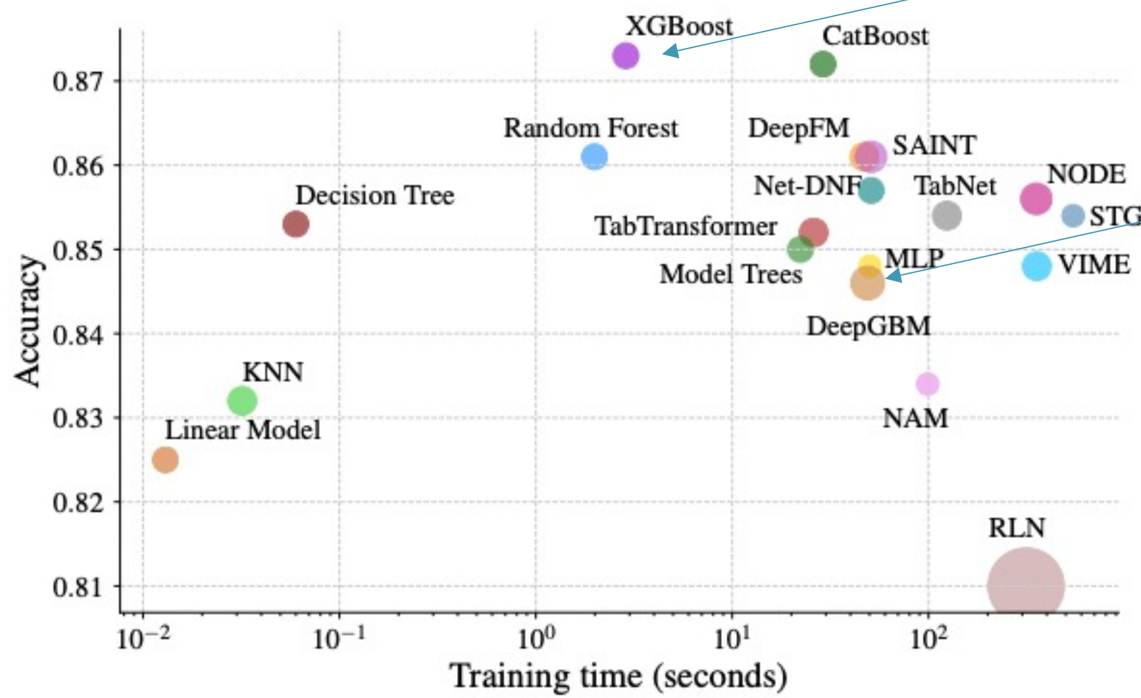
???

Why care about CARTs?

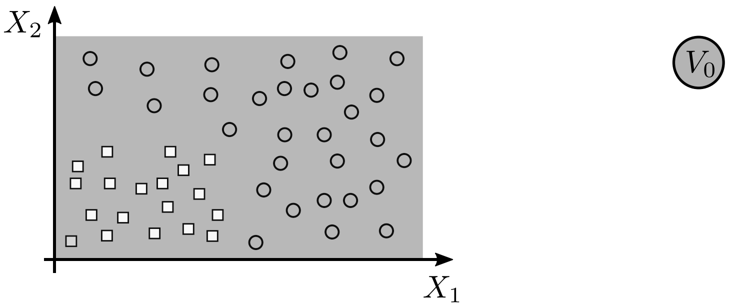
For tabular data

CART

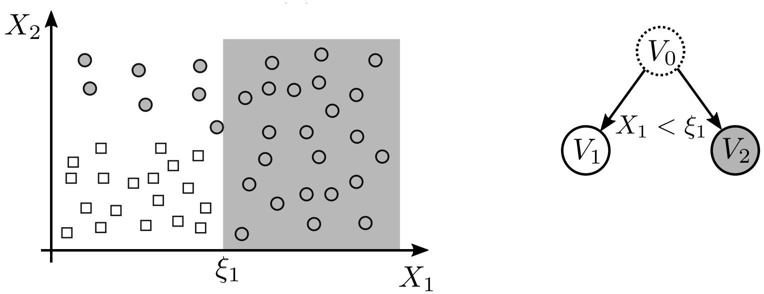
NN



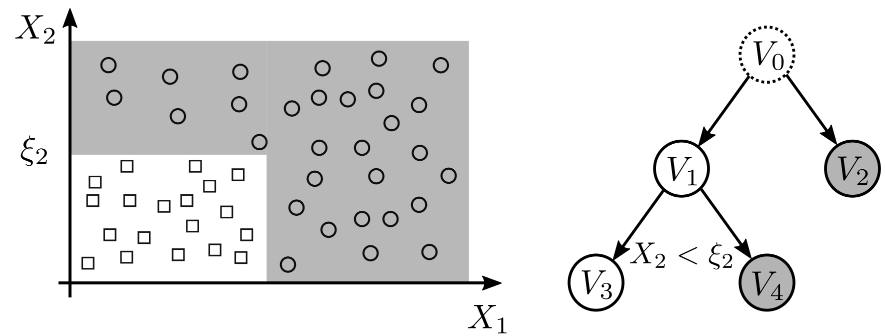
How a Decision Tree Classifier Works



(a) Initial state.



(b) First branch.

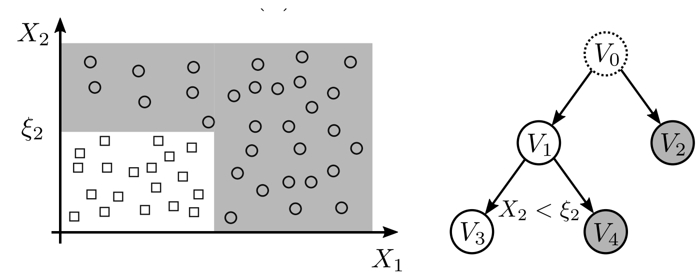


(c) Second branch.

Can inspect node structures to interpret model behavior -> Feature importance score (Interpretable)

Training a decision tree

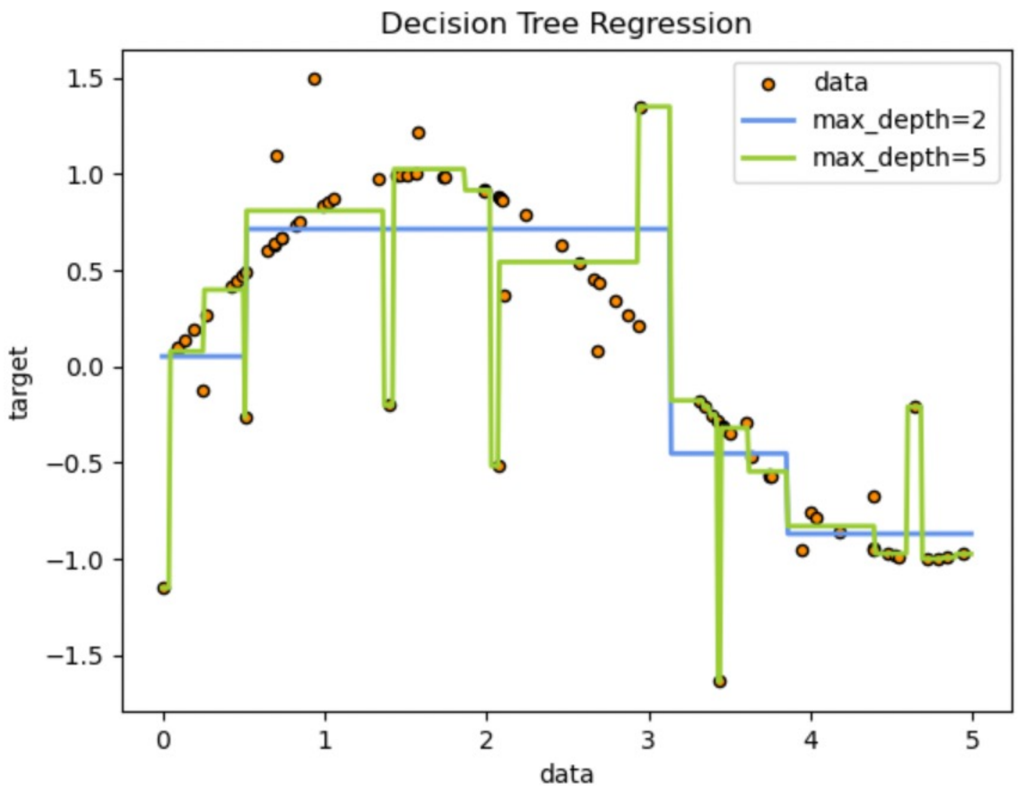
- Regression in logistic regression/deep learning
  - Find slope of function (weights) that minimize **error** between predicted and target variable.
- Classification in logistic regression/deep learning
  - Find slope of function (weights) that maximizes the likelihood of predicted variable.
- Regression in a decision tree
  - Find a split that maximizes "purity"
  - Related to variance
- Classification in a decision tree
  - Find a split that maximizes "information gain"
  - Related to entropy



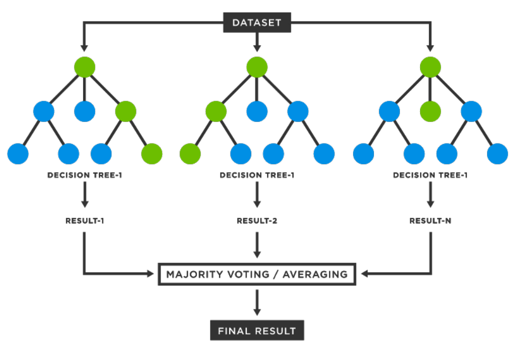
(c) Second branch.

Background in information theory (EE) needed to further understand this

Decision Tree Regression



- Decision tree regressors are may be less suitable for smooth functions
- Not suitable for extrapolation
- Prone to overfitting
  - Rectify with ensemble methods



Conclusions

- Why researchers care about AI/ML?
- How does supervised learning work?
- How does a logistic regression/NN work?
- How to train/test these models in practice?
- Should we care about Non-NN Models?
- **Next lecture: How have these models between applied to wildfire problems?**

Thank You

Me 375: Wildfire Science

ML Applications

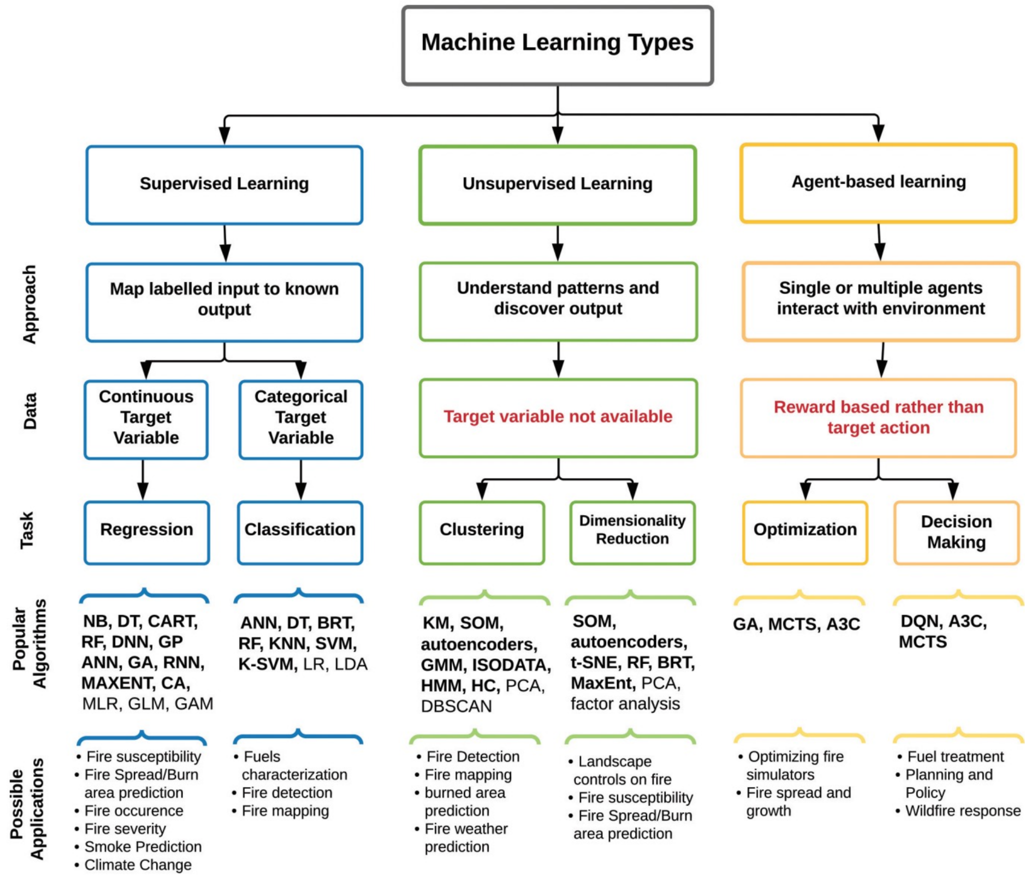
Wai Tong Chung

FxLab Stanford University
Mechanical Engineering

Agenda

- Last lecture: Fundamentals
- This lecture: Applications, Opportunities, Challenges
  - When to use ML
  - Past ML applications in Wildfires
  - Current ML Trends in Wildfires
  - Open Research Problems

Machine Learning for Wildfires



P. Jain et al. Env. Rev. (2020)

Let’s zoom in

Possible Applications

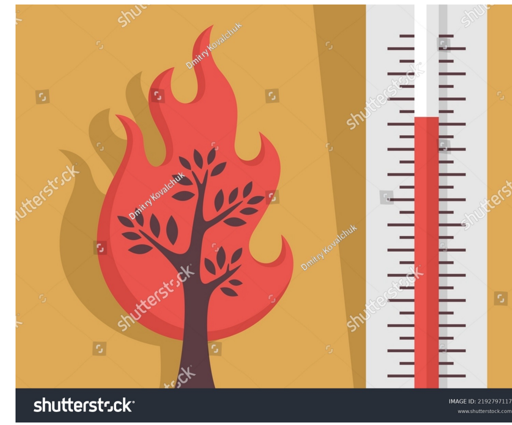
- Fire susceptibility
- Fire Spread/Burn area prediction
- Fire occurence
- Fire severity
- Smoke Prediction
- Climate Change
- Fuels characterization
- Fire detection
- Fire mapping

Supervised learning - Preidictions

Classification

Which leaf is burning?
Ans:
Leaf 1, leaf 2, leaf 3 …

Regression

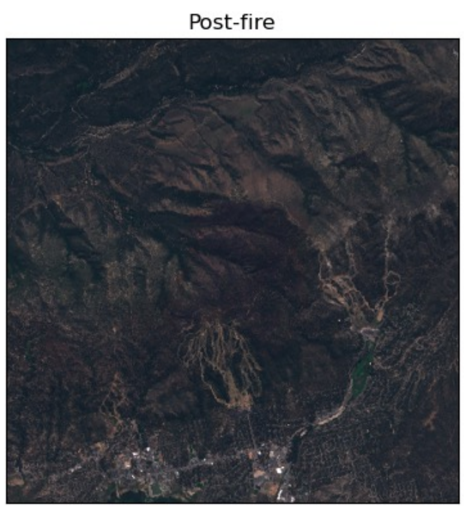


How hot is my tree?
Ans:
Leaf 1 is 735.222,
Leaf 2 is 314.159…

When and how is this useful in the sciences?

When to use ML

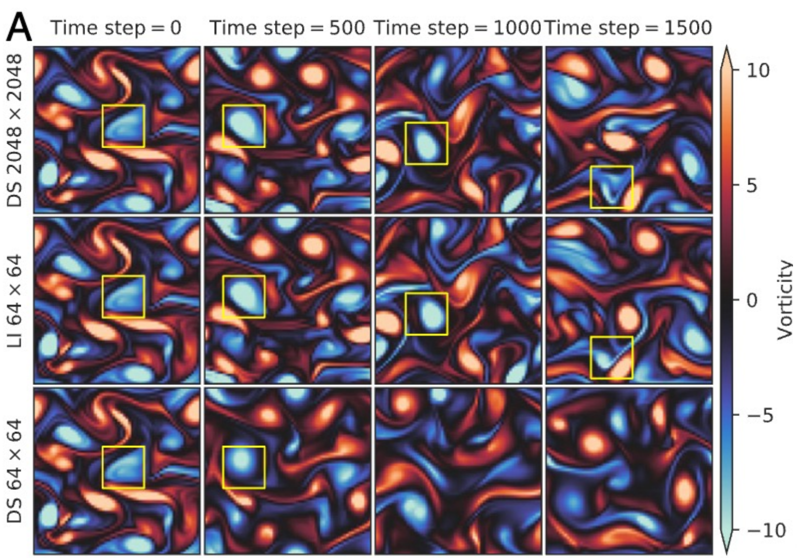
- No reliable relations

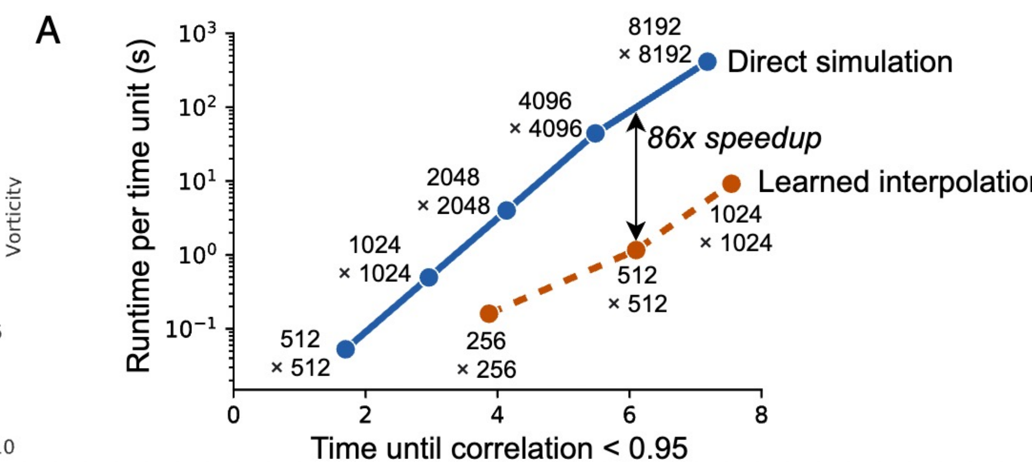


Fire spread rate from satellite images?

When to use ML

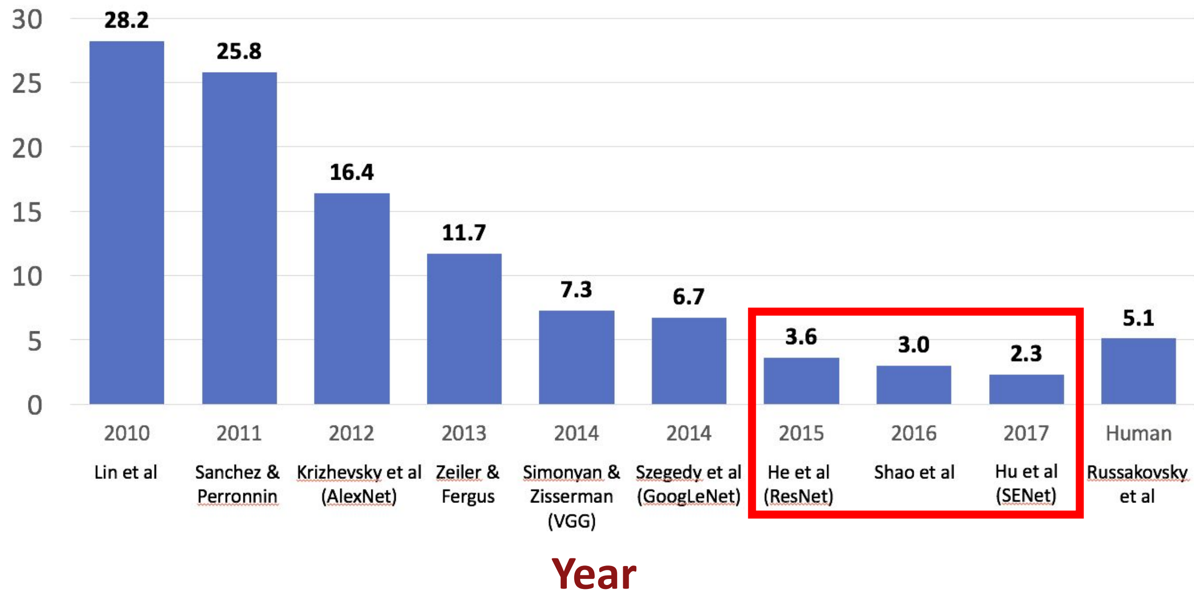
- Costly! -> ODEs/PDEs are expensive to calculate





When to use ML

Universal Approximators: **Typical ML Error**



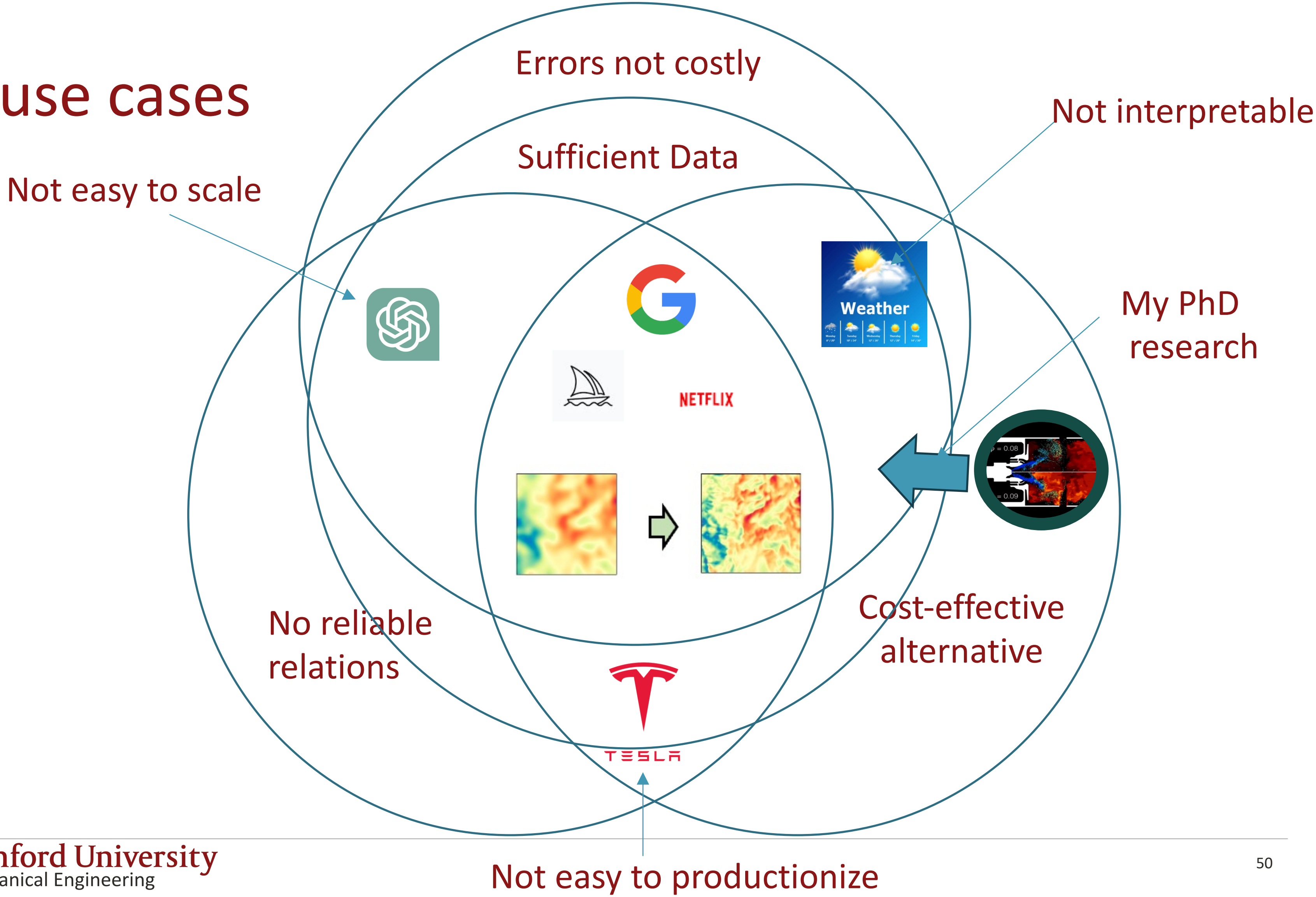
Can I trust ~3% ML error when driving a car?

Tesla behind eight-vehicle crash was in 'full self-driving' mode, says driver

San Francisco crash is the latest in a series of accidents blamed on Tesla technology, which is facing regulatory scrutiny

Errors must not be too costly!

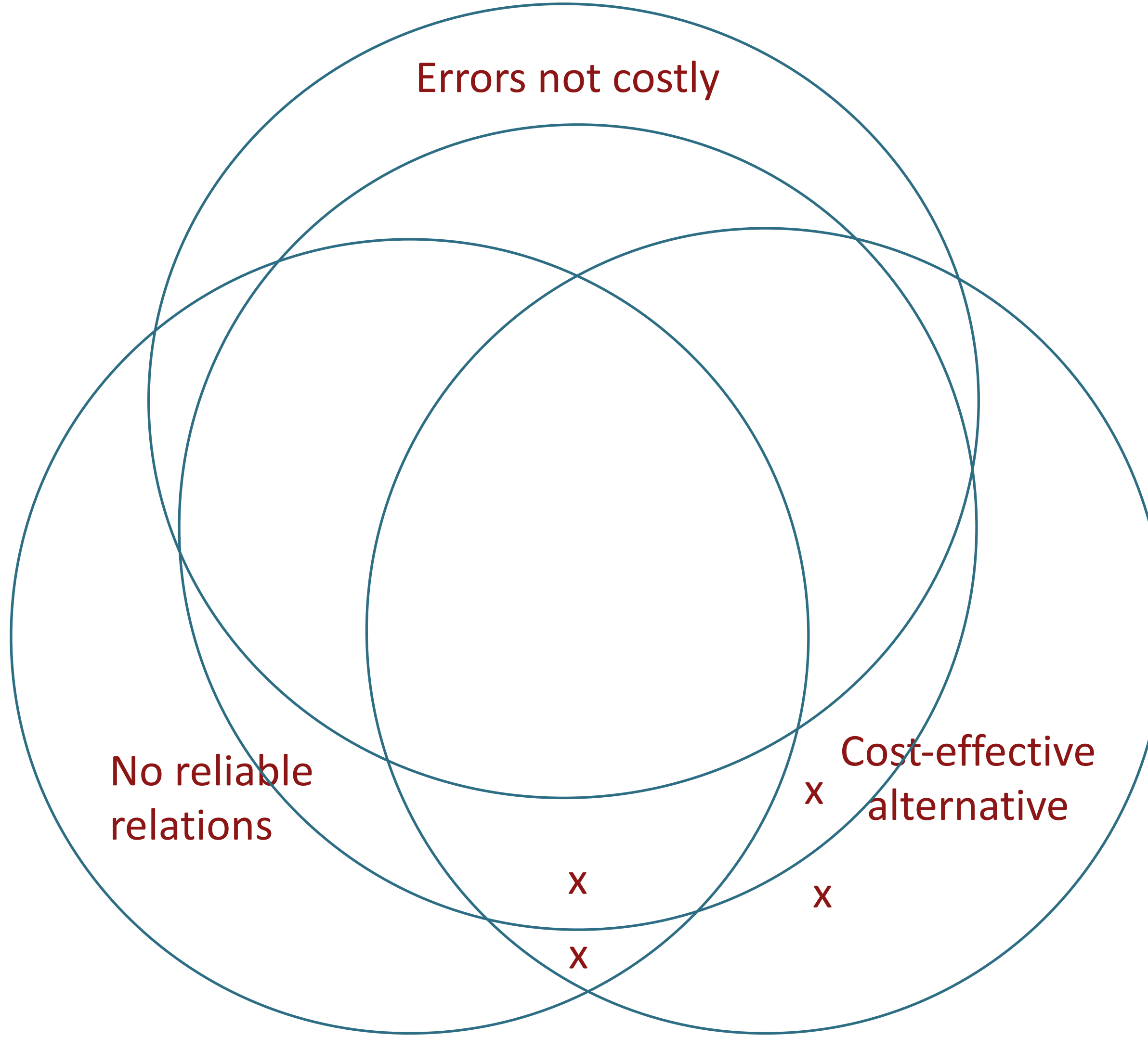
ML use cases


Errors not costly
Sufficient Data
Not interpretable
Not easy to scale
Weather
NETFLIX
My PhD research
No reliable relations
Cost-effective alternative
TESLA
Not easy to productionize

ML use cases

Possible Applications

- Fire susceptibility
- Fire Spread/Burn area prediction
- Fire occurence
- Fire severity
- Smoke Prediction
- Climate Change
- Fuels characterization
- Fire detection
- Fire mapping

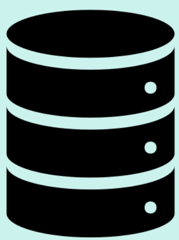


- Sims. are expensive
- Satellite/Aerial image analysis is highly empirical
- Data sources are separate

What are challenges in applying ML to the wildfires?

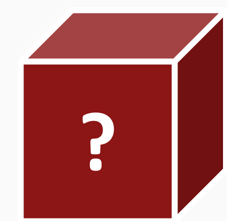
- Lack of Structured Datasets
  – separate images, sensor data, observational, sim. data
- Insufficient reliability
  - Errors from ML models
  - Insufficient interpretability

Data challenges



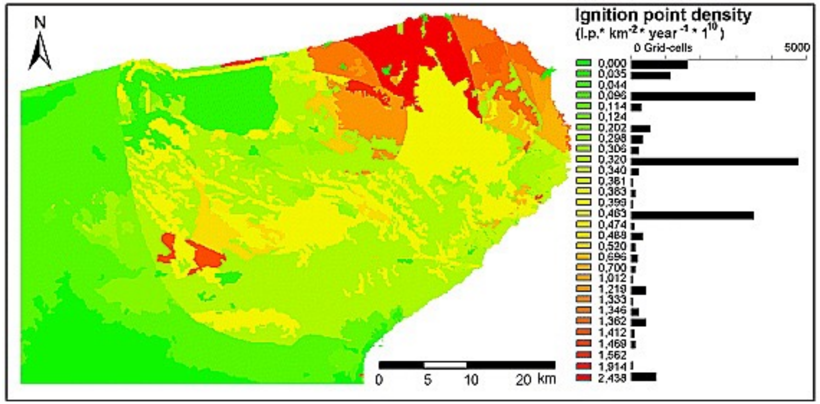
ML Errors

Black-box



Wildfire Risk

Fire ignition points (1997–2003), were used to derive a fire occurrence map through a kernel density approach.



Data provided by the Italian National Database:

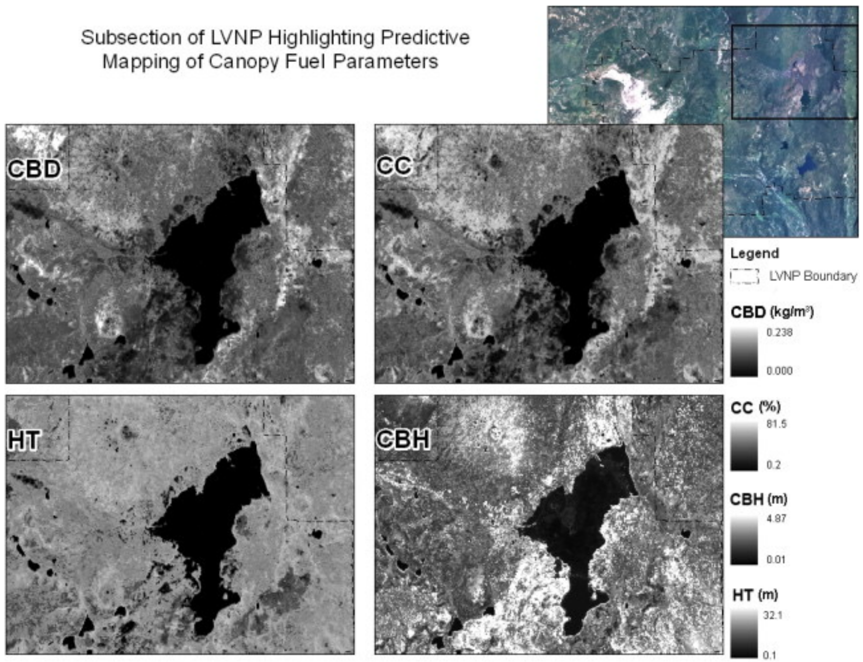
continuous urban fabric, discontinuous urban fabric, industrial or commercial units, port areas, mineral extraction sites, nonirrigated arable land, permanently irrigated land, vineyards, olive groves, pastures, annual crops associated with permanent crops, complex cultivation patterns, agriculture land with significant areas of natural vegetation -, broadleaf forest, coniferous forest, mixed forest, natural grasslands, Sclerophyllous vegetation, transitional woodland-shrub, bare rocks, sparsely vegetated areas, salt marshes, water bodies, average temperature of warmest month, average temperature of coldest month, annual average minimum temperature, annual average temperature, annual average rainfall, altitude, annual average maximum temperature, population distribution by CORINE (CLC90), aspect divided in 8 classes + 1 for the flat areas, Slope, mask with Gargano National Park limits, continuous grid distance from secondary roads, continuous grid distance from primary roads, illumination factor

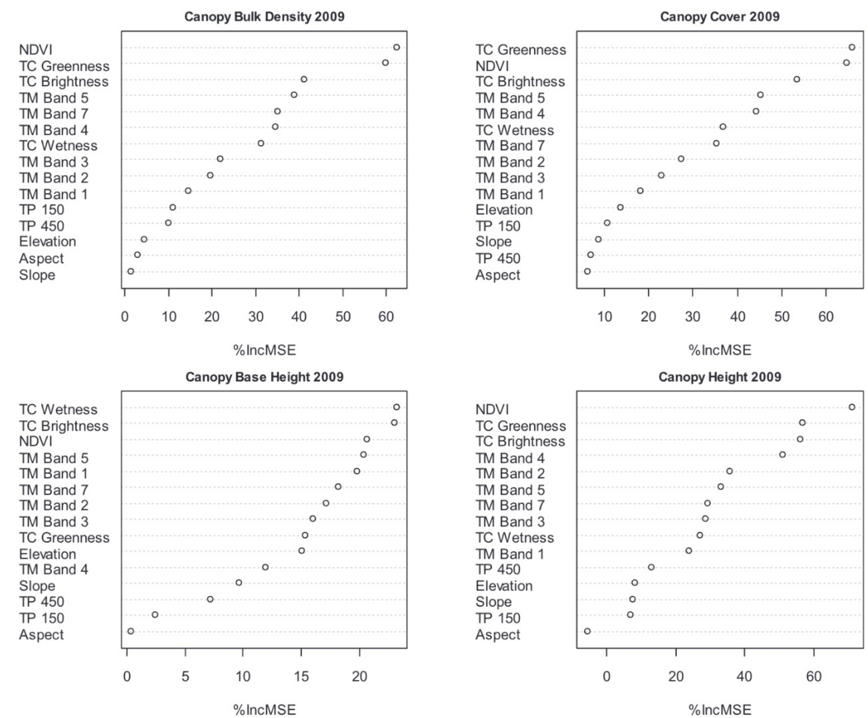
- **Govt Datasets** are impressive
- No discussion on overfitting
- Feasibility study on ML
- Decision tree feature importance is useful
- Prior to ML popularity (2006)

Pierce et. al. Use of random forests for modeling and mapping forest canopy fuels
for fire behavior analysis in Lassen Volcanic National Park, California, USA. *For. Ecol. Manag.* (2012)

Fuel Characterization + Fire Severity

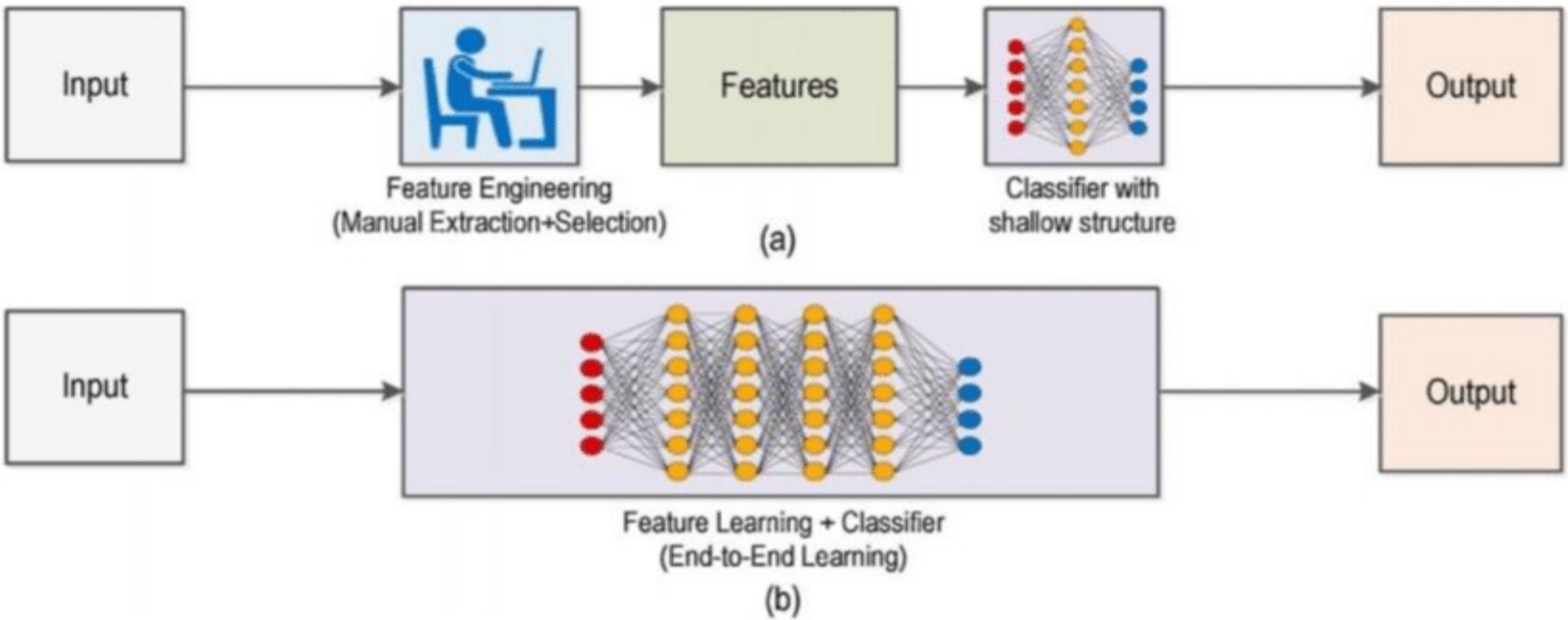
Mapping Satelite images to Canopy Bulk Density (CBD), Canopy Cover (CC), Canopy Base Height (CBH), and canopy Height (HT)





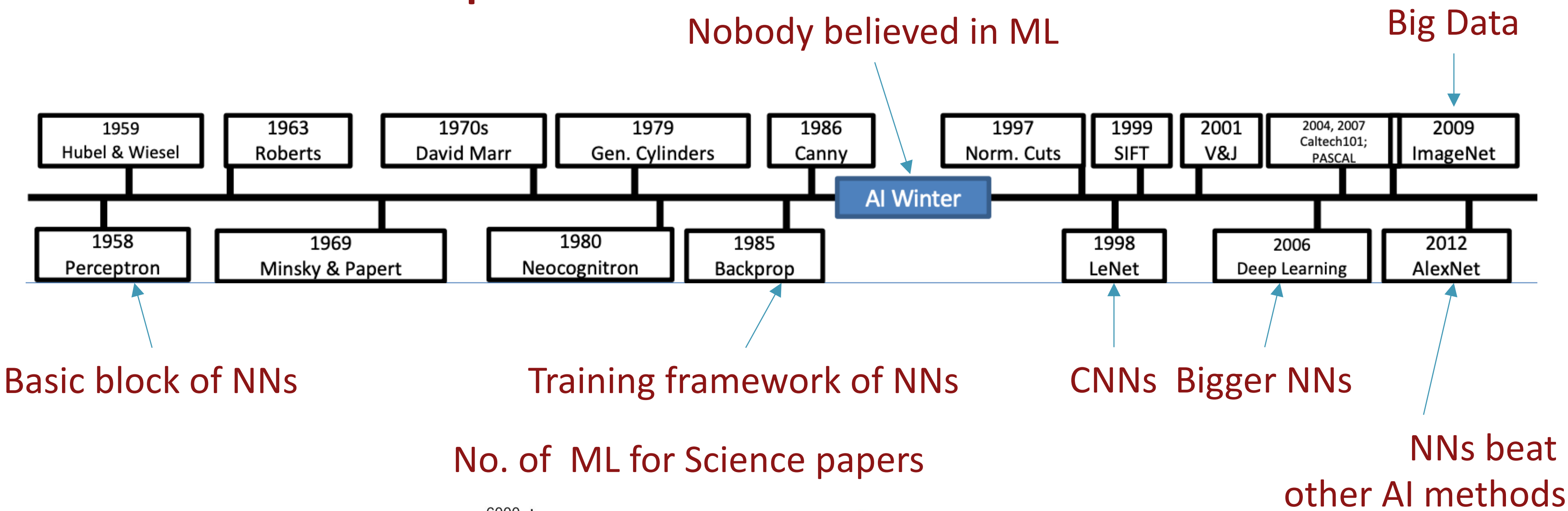
- LANDSAT data – Open-source since 2008
- r^2 values ranging from 0.55 to 0.68
- No train-test split, overfitting discussion

Two paradigms of ML

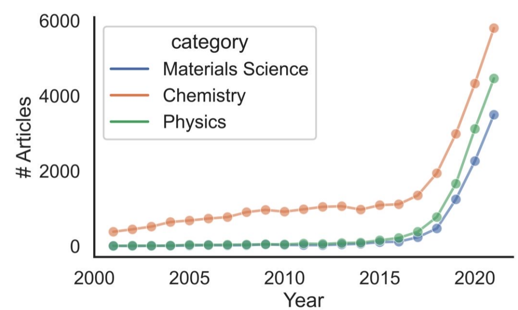


del Real et al. (2020)

Previous work predate interest in ML!



No. of ML for Science papers



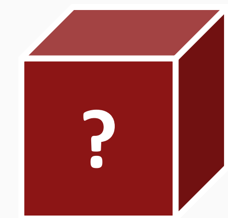
L. Fei-Fei et. al., CS231N (2023)

Early Work

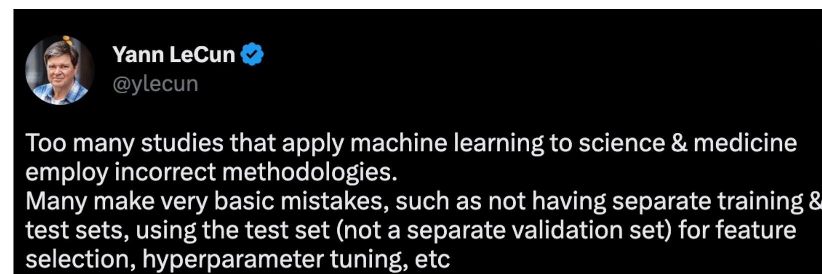
- Demonstrate proof-of-concept
- Demonstrate potential use of ML models
- Not too sophisticated
  - Labels generated by Government Authorities
  - Train on Satellite images
  - Use interpretable ML
  - Find Useful features
- **Probably overfitting**
- What can we do with more data?

Challenge tackled:

Black-box



Tweet from 2022



Yann LeCun
@ylecun

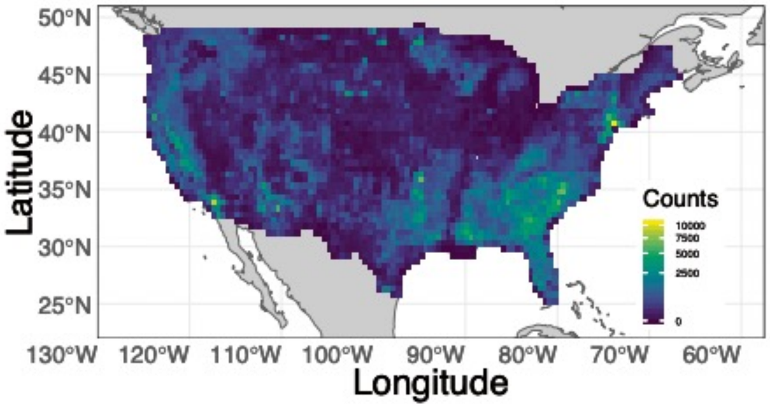
Too many studies that apply machine learning to science & medicine employ incorrect methodologies.
Many make very basic mistakes, such as not having separate training & test sets, using the test set (not a separate validation set) for feature selection, hyperparameter tuning, etc

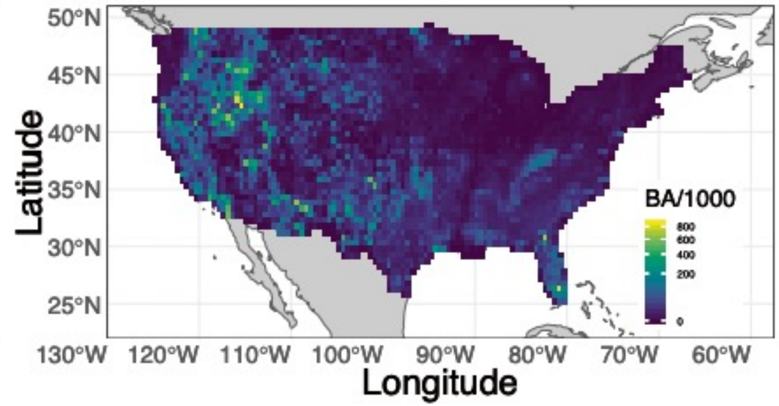
We are still early in ML adoption!

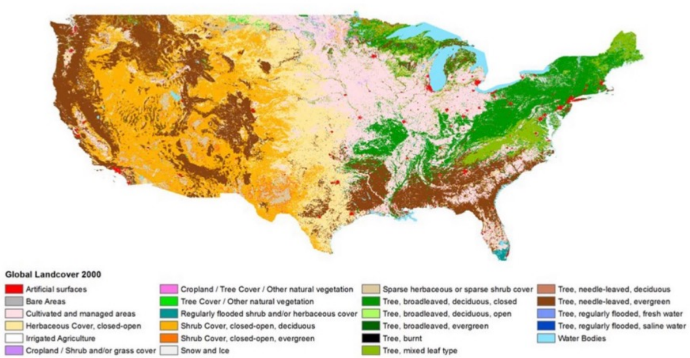
Current Trends

Data, data, data

EVA 2021 Challenge - Prediction of Fire occurrences







Data from various sources aggregated by U.S. Forest Service (Short, 2017)

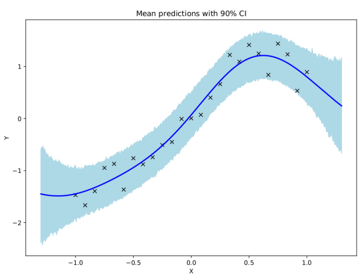
Team name	S_{CNT}	rank_{CNT}	S_{BA}	rank_{BA}	S_{total}	rank_{total}	SI paper
BlackBox	2805	1	3316	1	6121	1	Ivek & Vlah
Kohrrelation	2990	3	3446	3	6436	2	Koh
Bedouins	3146	4	3408	2	6554	3	Hazra et al.
KUNGFUPANDA	3166	5	3513	5	6679	4	Makowski
RedSea	3419	7	3467	4	6886	5	Zhang et al.
NaiveTom	3403	6	3565	7	6968	6	–
THEFIRETASTICFOUR	2979	2	4133	11	7111	7	–
EdX	3520	8	3595	8	7115	8	–
SNUBRL	4074	9	3530	6	7604	9	Kim et al.
MayLaB	4418	11	3765	10	8182	10	–
LancasterDucks	4926	12	3719	9	8645	11	D'Arcy et al.
FUFighters	4329	10	4863	13	9191	12	–
BENCHMARK	5565	13	4244	12	9810	13	–

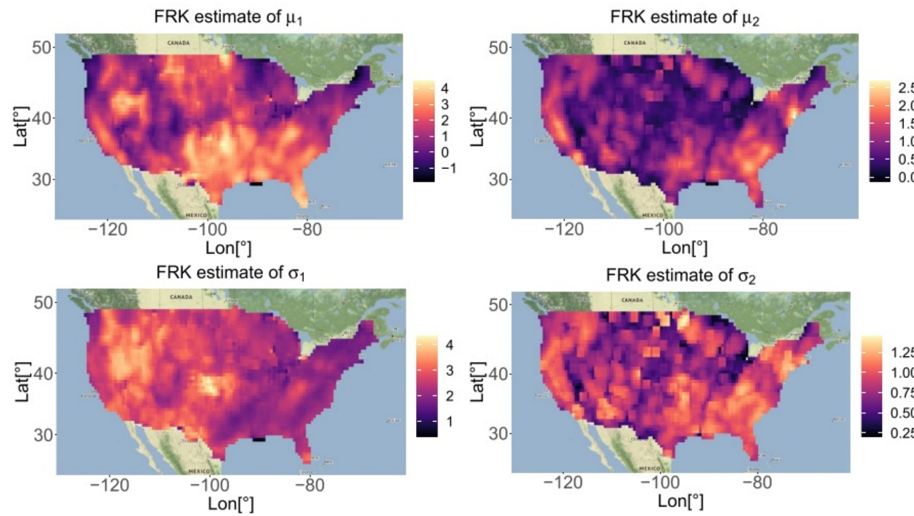
Cisneros *et. al.* A combined statistical and machine learning approach for spatial prediction of extreme wildfire frequencies and sizes. Extremes (2023)

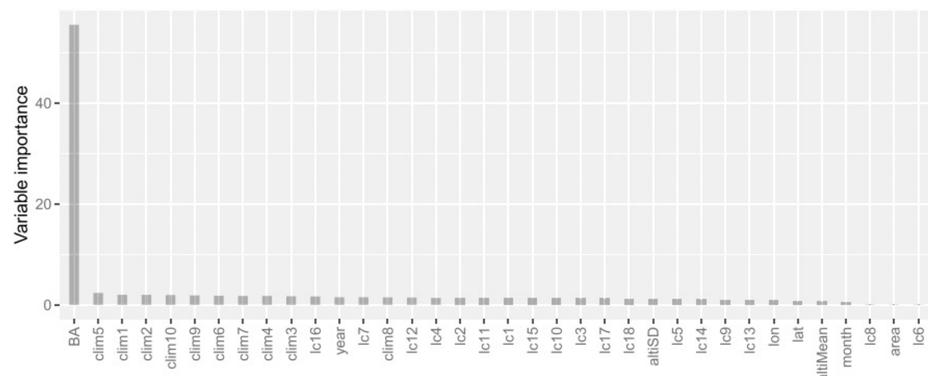
3rd Place winner

Part of a ML Competition/Challenge:

1. Use Gaussian Process Model to estimate statistics from classification
2. Process the generated statistics
3. Use random forests to predict fire occurrence

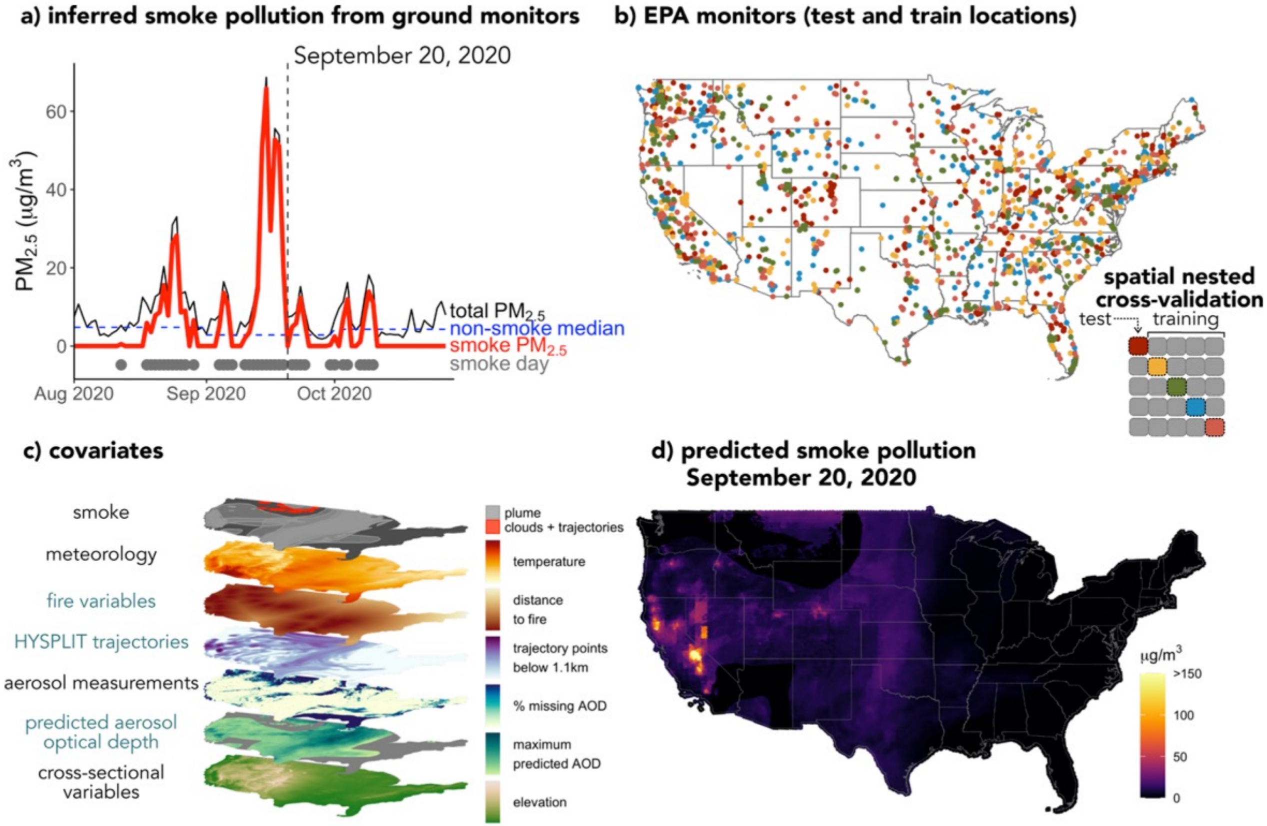






- Train-test split with cross-validation
- Lost to 2 pure ML teams
- Feature importance show pre-processing is somewhat flawed
- Multicollinearity?
- If it looks stupid but works, it isn't stupid

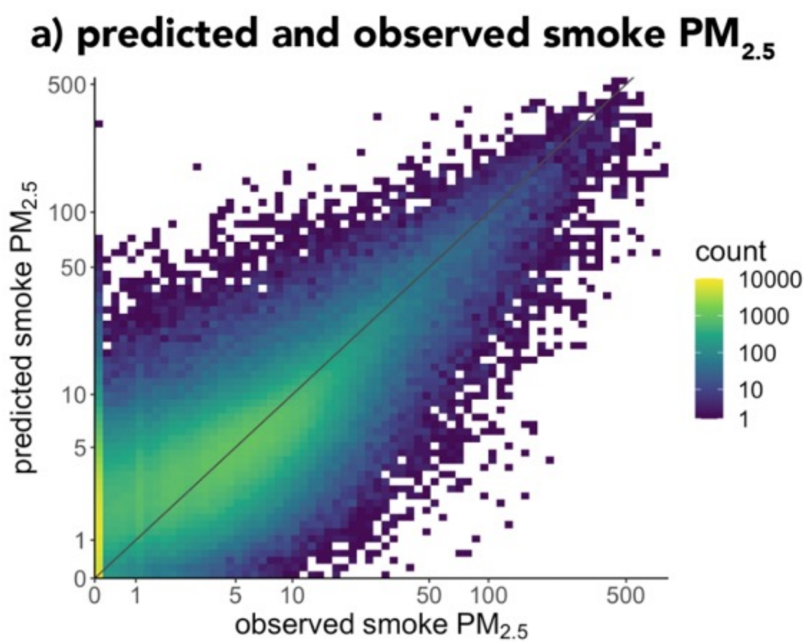
More modern take on regression

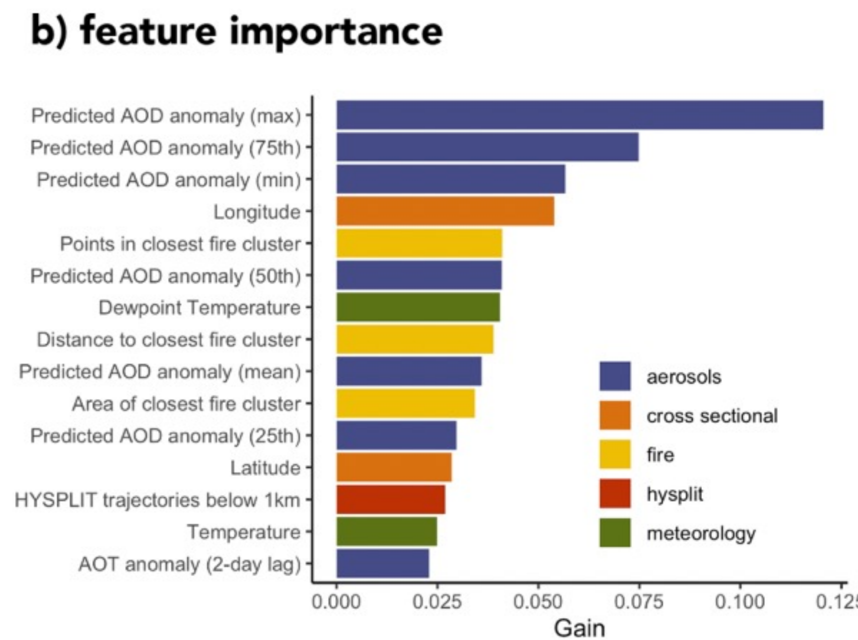


1. Curate Monitor, Sensor, Weather, Satellite data
2. Use **Gradient Boosted Trees**
3. Label small subset of data
4. Apply to 10 years of U.S geo/weather data.
5. Estimate soot emissions in U.S from past 10 years.

- Laborious effort in data collection
- Still using CARTs!

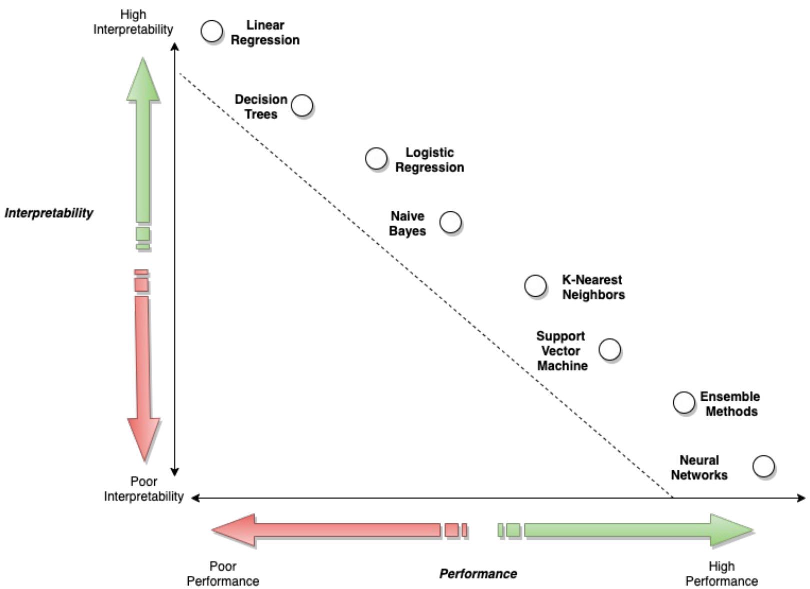
Results

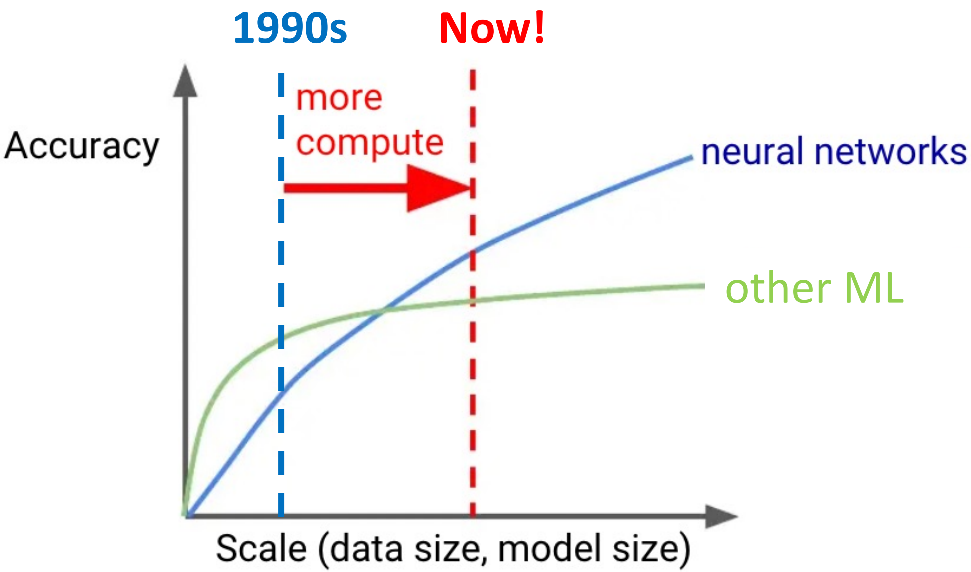




People really care about feature importance!

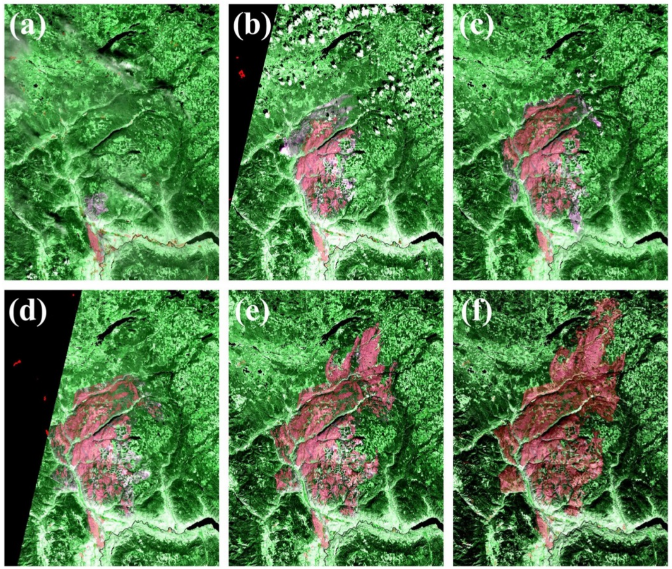
Two important charts driving AI for Science





Jeff Dean, Lecture for YCombinator AI (2017)
Amazon. White Paper (2021)

Real-time prediction!

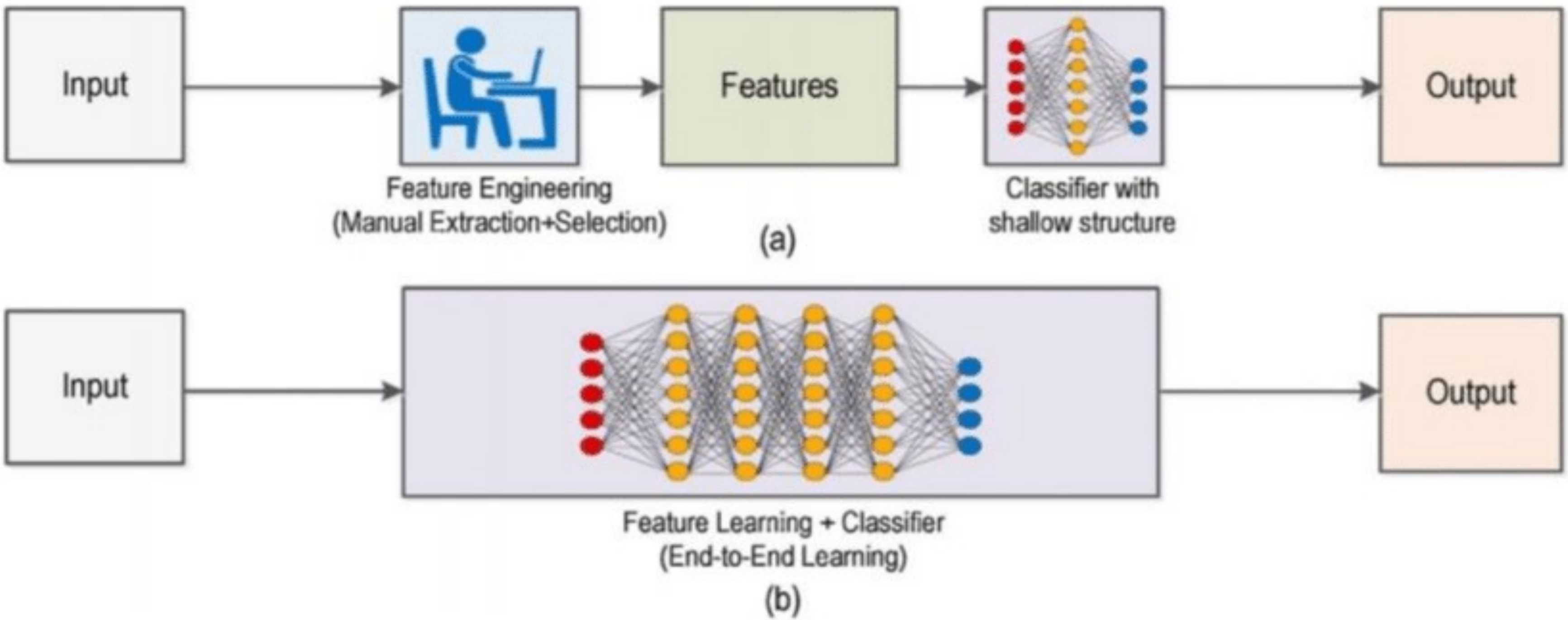


Can beat traditional stats methods

- deep learning can leverage large satellite datasets.
- Compute powerful enough for real-time prediction

						Accuracy	Cohen's	
Sat.	**Data**	**Method**	**Seg.**	**Precision**	**Recall**	**OA**	**Kappa**	**F_1**
S1	VH	**kmap**	>2	21.82%	65.13%	55.07%	0.1014	0.3269
	VV			45.21%	80.19%	67.02%	0.3404	0.5782
	VH, VV	**kmap**	>2	51.17%	82.11%	70.01%	0.4002	0.6305
	VH, VV	**CNN_mrg**	Otsu	**71.82%**	93.91%	**83.58%**	**0.6716**	**0.8139**
		CNN_tsc_mrg		70.60%	**95.07%**	83.47%	0.6694	0.8103

Two paradigms of ML

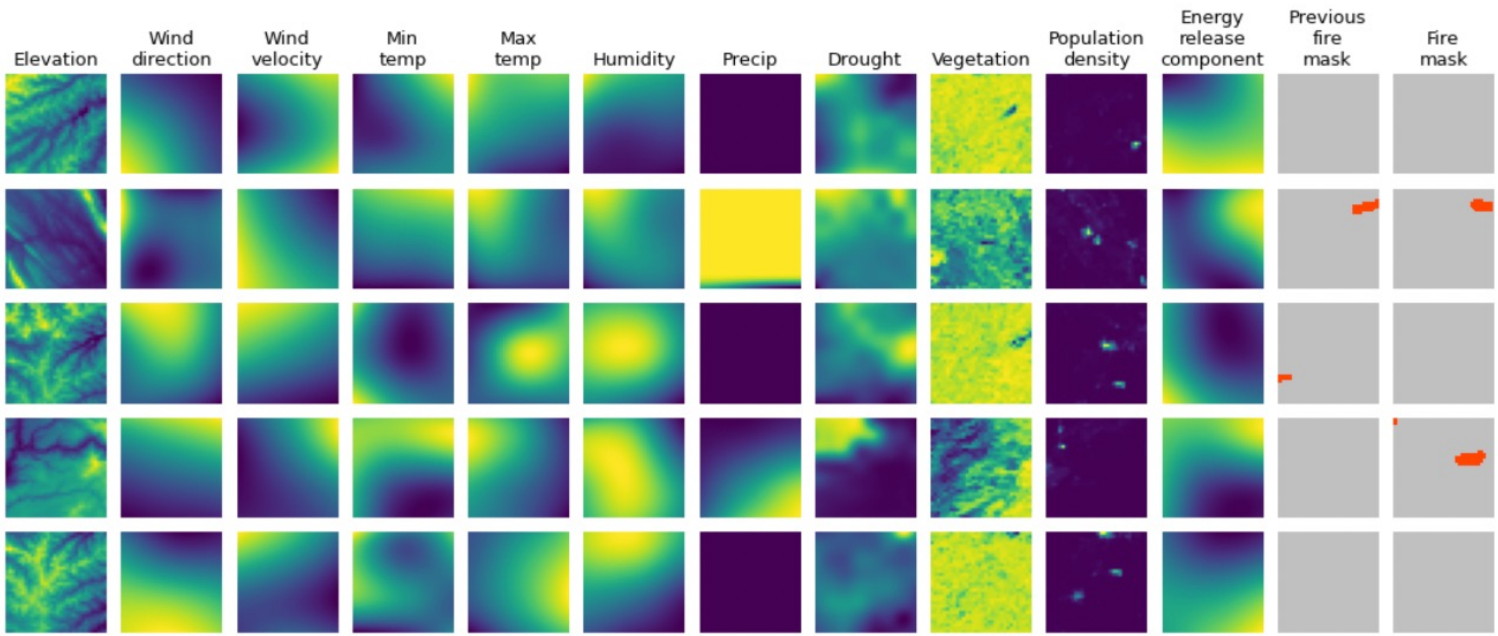


del Real et al. (2020)

Huot et al. Next Day Wildfire Spread: A Machine Learning Dataset to Predict Wildfire Spreading From Remote-Sensing Data. IEEE Trans. *IEEE Trans Geosci Remote Sens* (2022)

Partial Govt Open-source wildfire datasets

- Much of the previous work driven by data availability
- We are starting to see more data from all parties



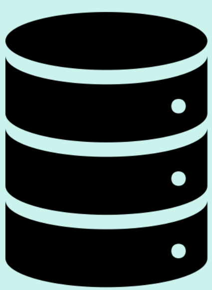
Data taken from Google Earth Engine + the Moderate Resolution Imaging Spectroradiometer (MODIS), the Visible Infrared Imaging Radiometer Suite (VIIRS), and the Shuttle Radar Topography Mission (SRTM)

Current State-of-the-art

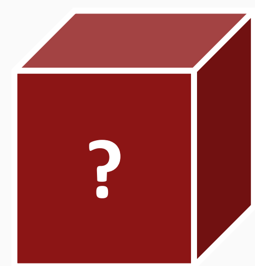
- Open-source resources enable a wider range of data access
- Researchers are starting to curate and structure unstructured data
- What’s next?

Focus of studies so far:

Data challenges



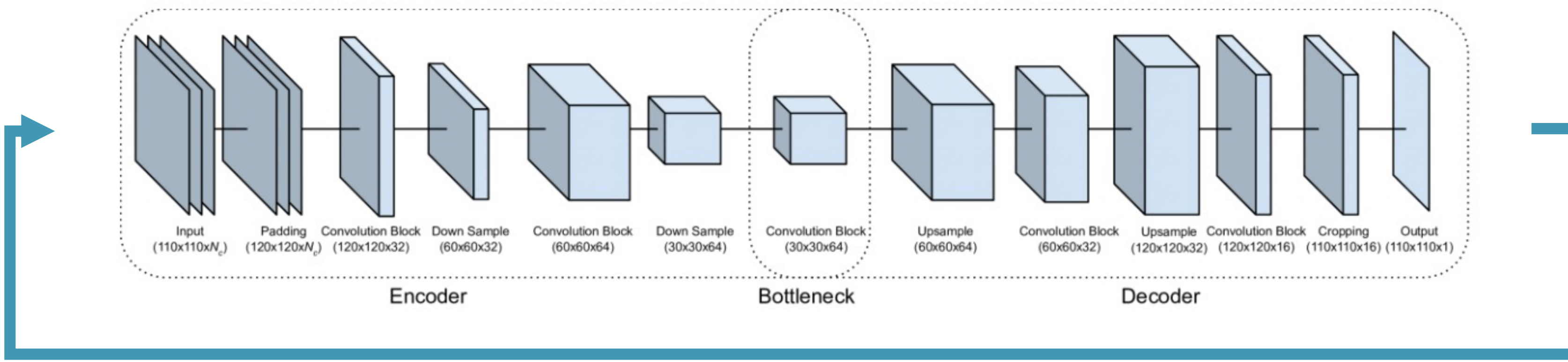
Black-box



Reliability!!

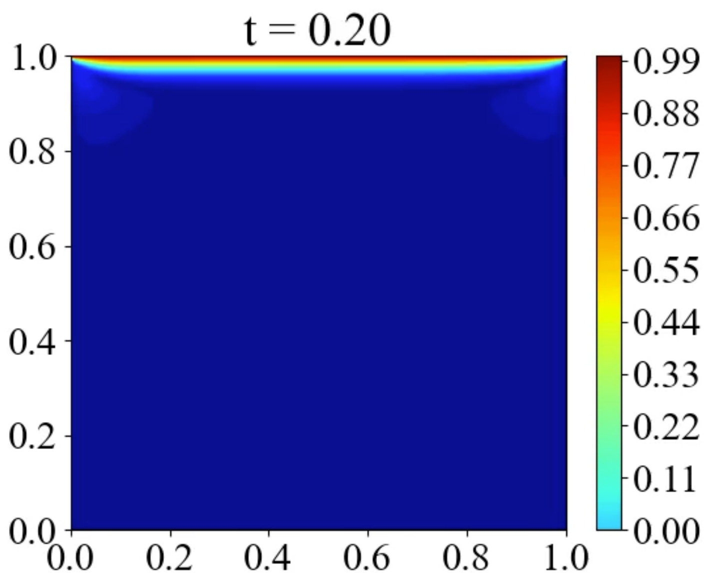
How do we get people to trust ML models?

Autoregressive modeling

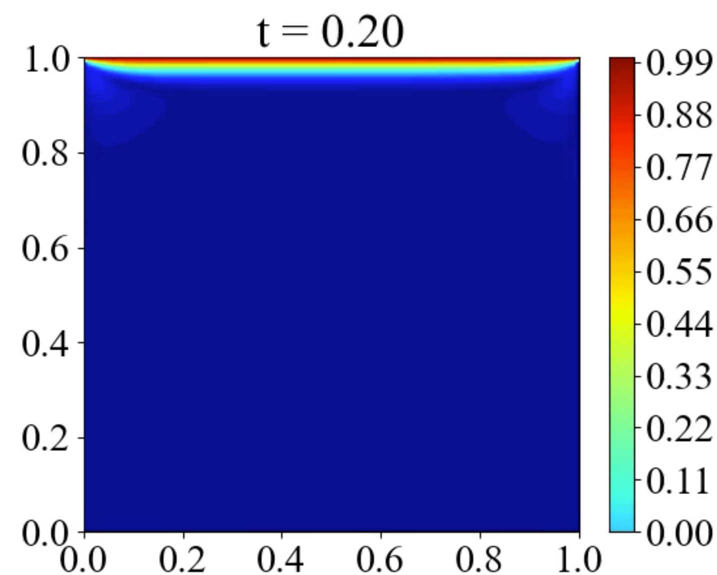


Sharma et al. A Review of Physics-informed ML in Fluid Mechanics. Energies (2023)

Problem with Autoregressive modeling



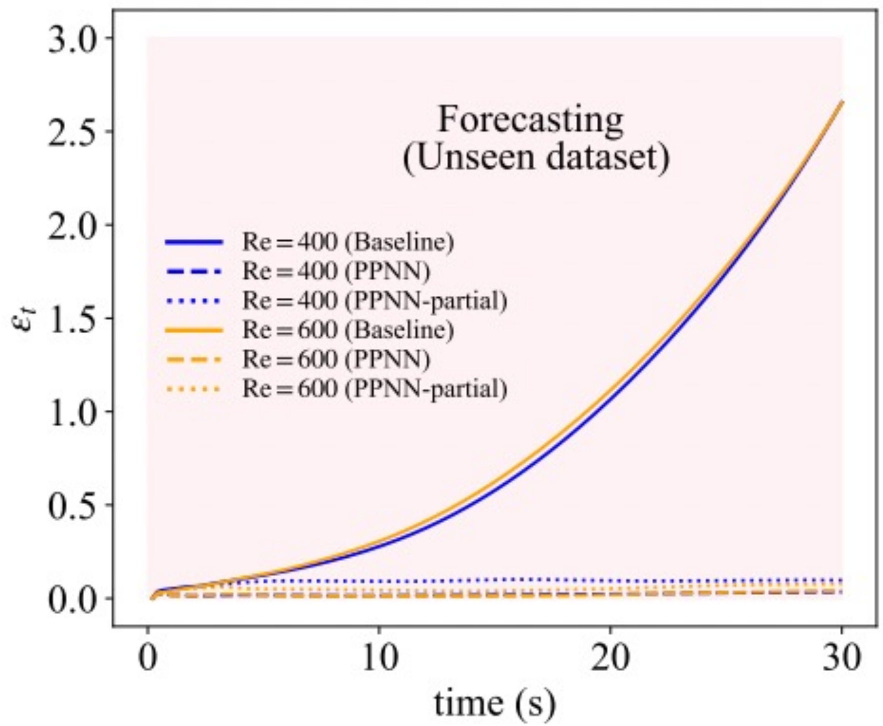
Incompressible Finite Difference Solver



ConvResNet (ML) Prediction

Why does this happen?

Problem with Autoregressive modeling

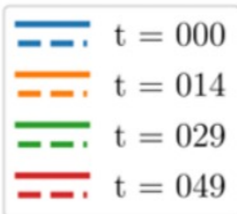


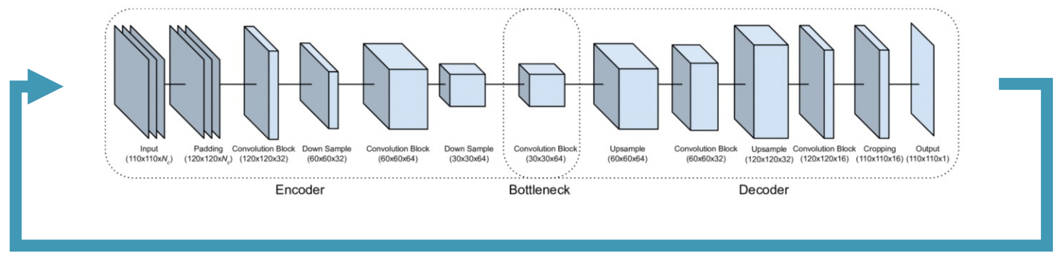
Some top researchers believe in better alternatives to LLMs for this reason

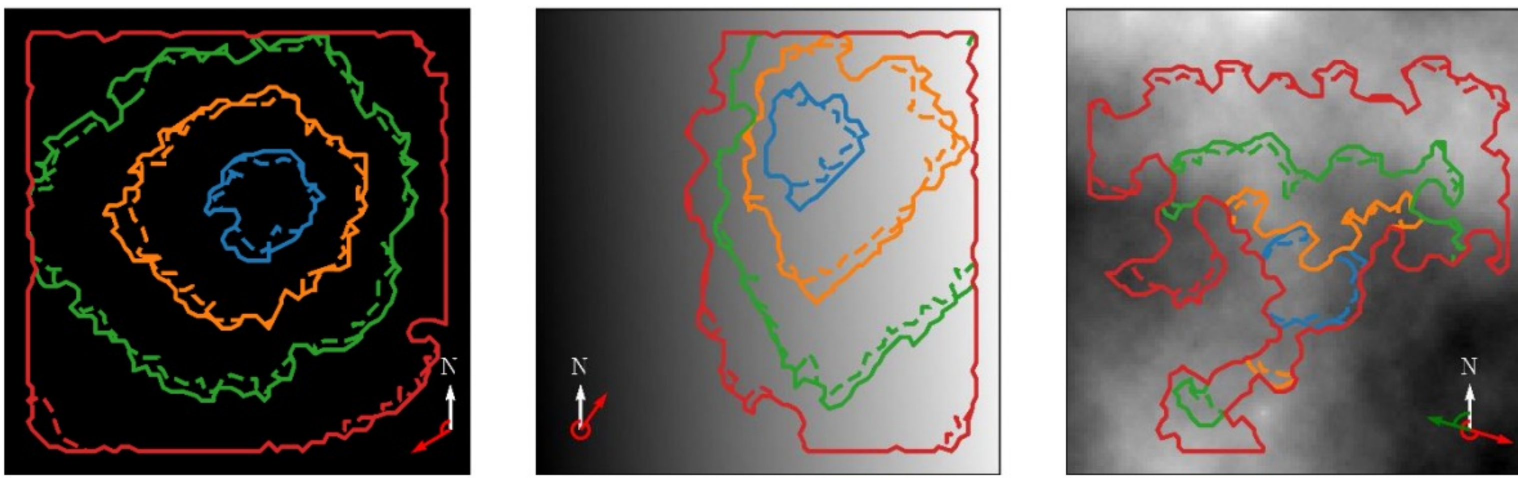
Time-dependent/Long-sequence predictions are hard

How do we address this?

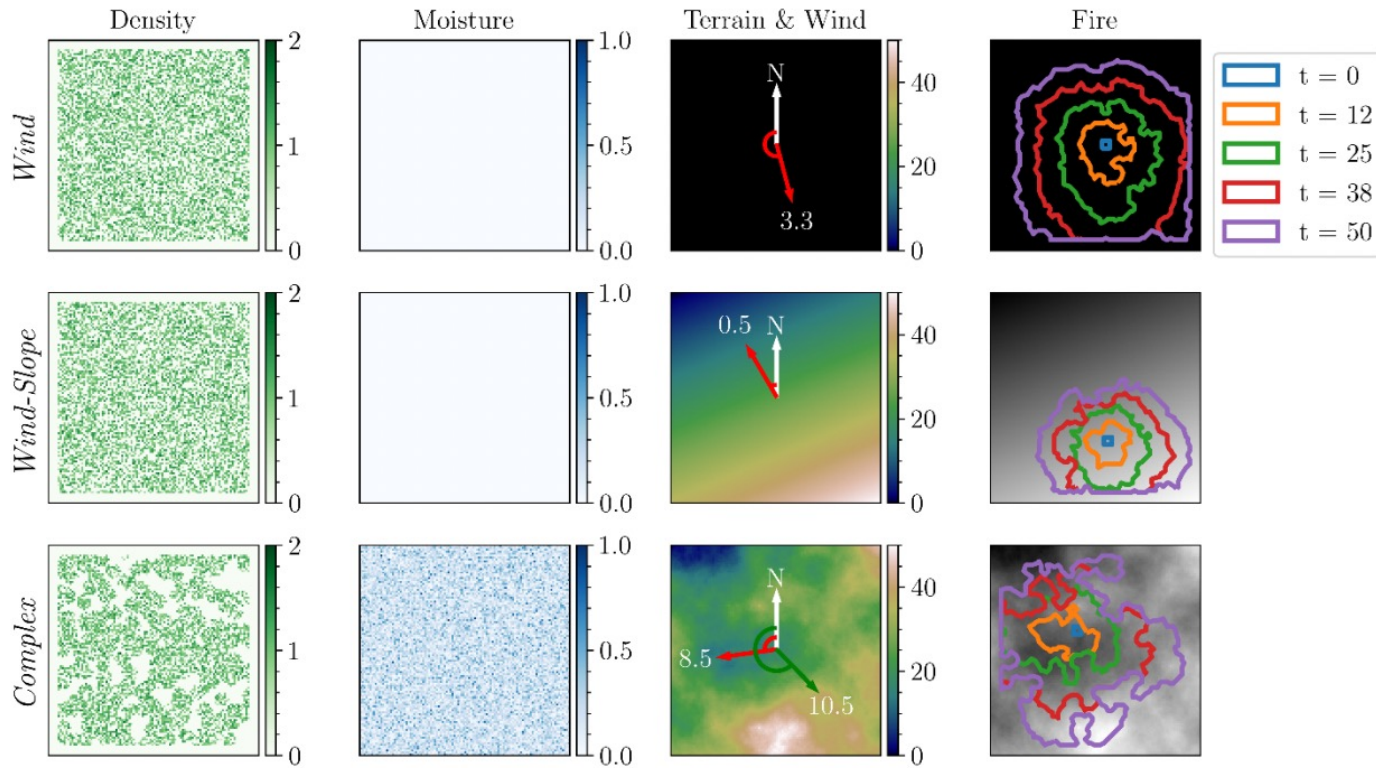
Next-frame fire-front prediction



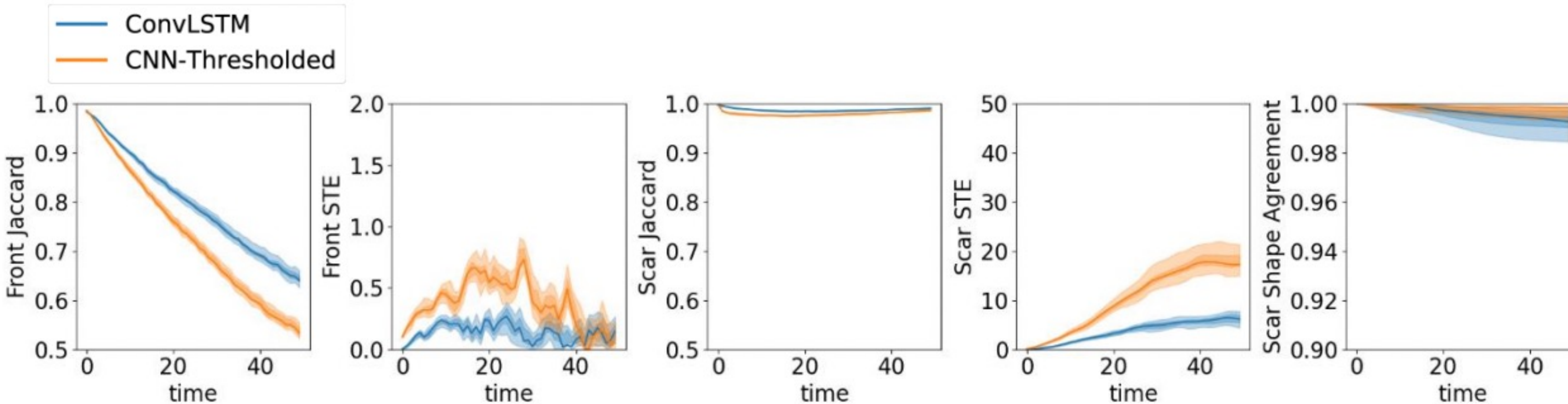




Fire Front Simulation Data



Conv LSTM

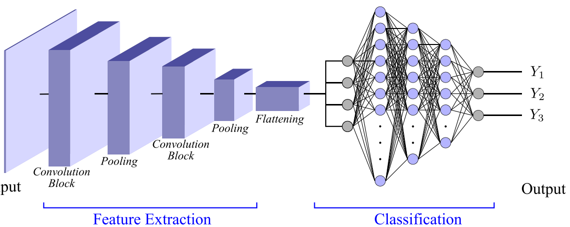


Why does the Conv LSTM work better?

Larger context windows!

ConvLSTM

Vision transformers are more parallelizable version of this



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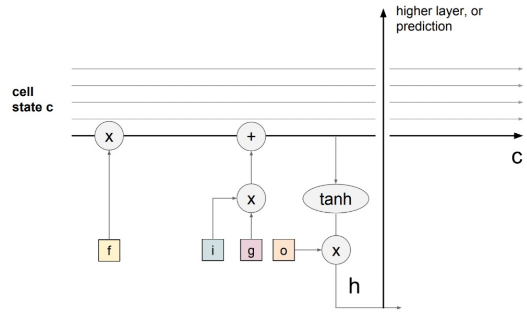

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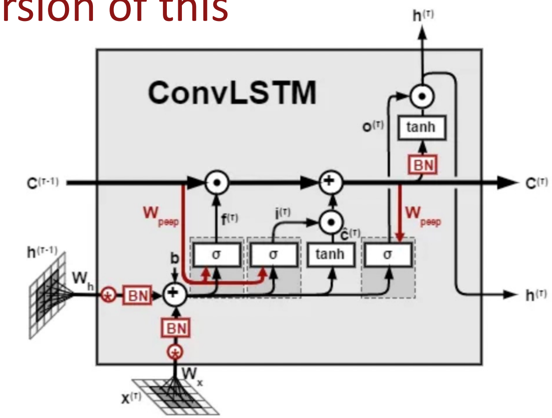


More stable version of this

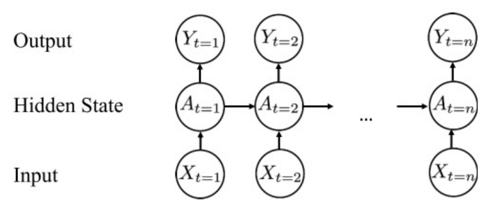


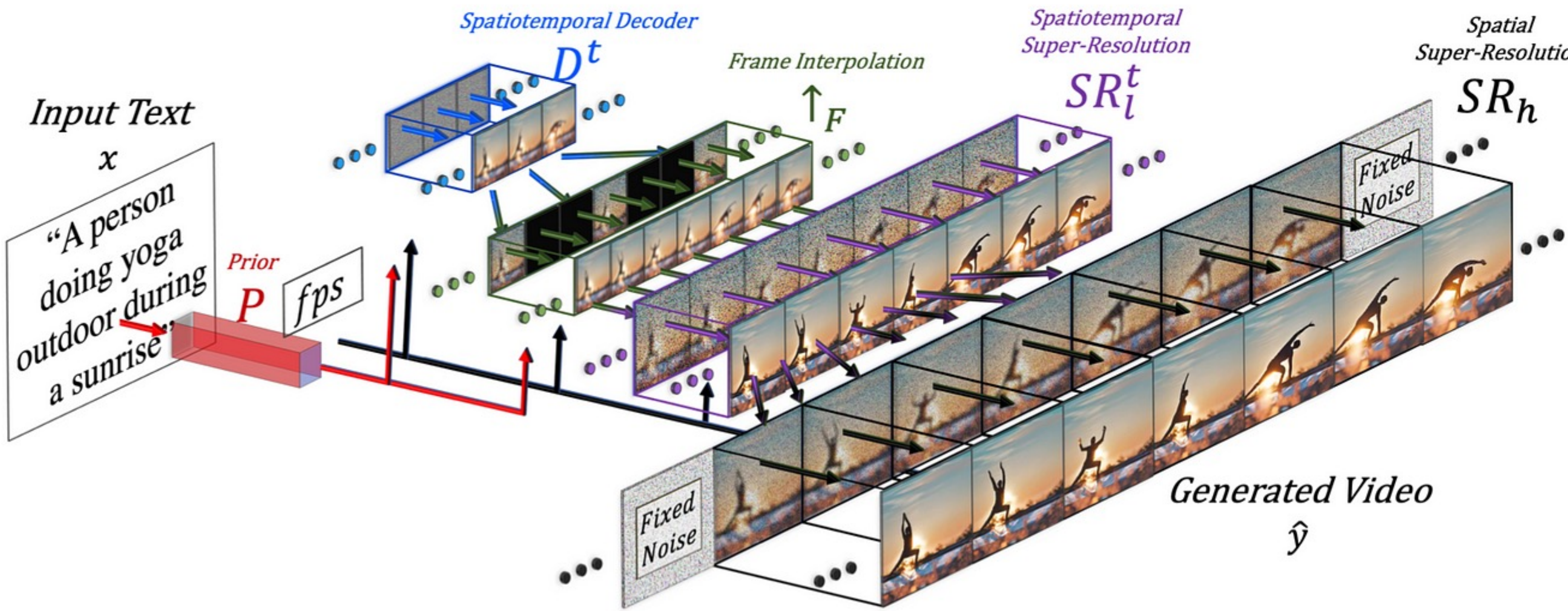
Fig. 16. Schematic of a many-to-many RNN.

- Has memory from the previous time steps
- Only 10 snapshots - Still using autoregression
- Why?

Limited memory!

A100 GPUs have 40GB

Taking context windows to the asymptote



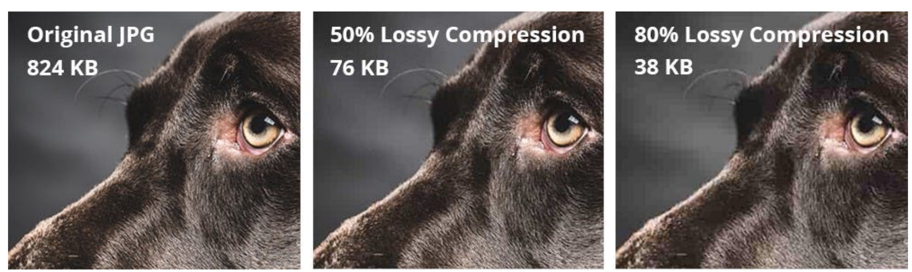
Hu (2022) https://towardsdatascience.com/generative-ai-878909fb7868

Turn 2D + time into a 3D block

Still have issues with memory

Dealing with memory

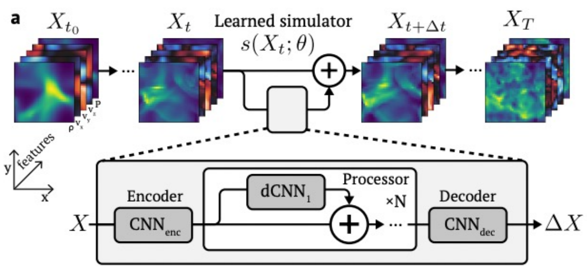
NVIDIA Blog (2021)

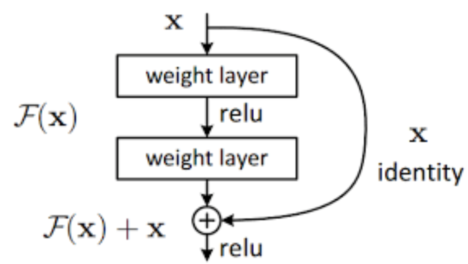


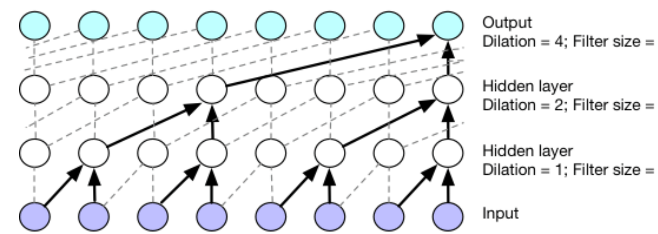
https://hackernoon.com/using-ai-to-super-compress-images-5a948cf09489

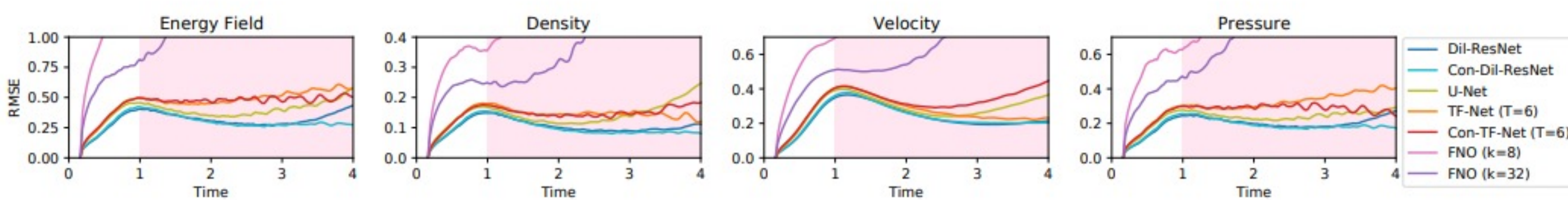
Another Pure ML Approach

Use of residual blocks, dilated layers, optimal timestep help

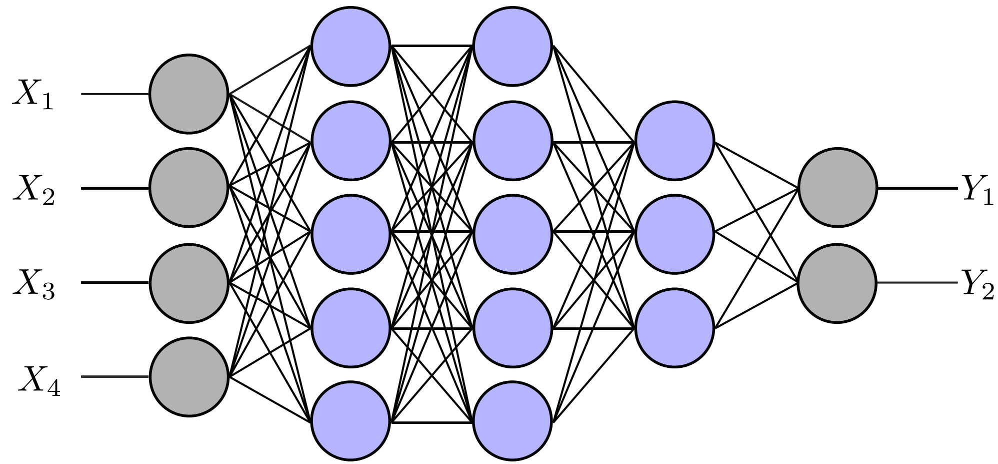








Basically Hyperparameter Search

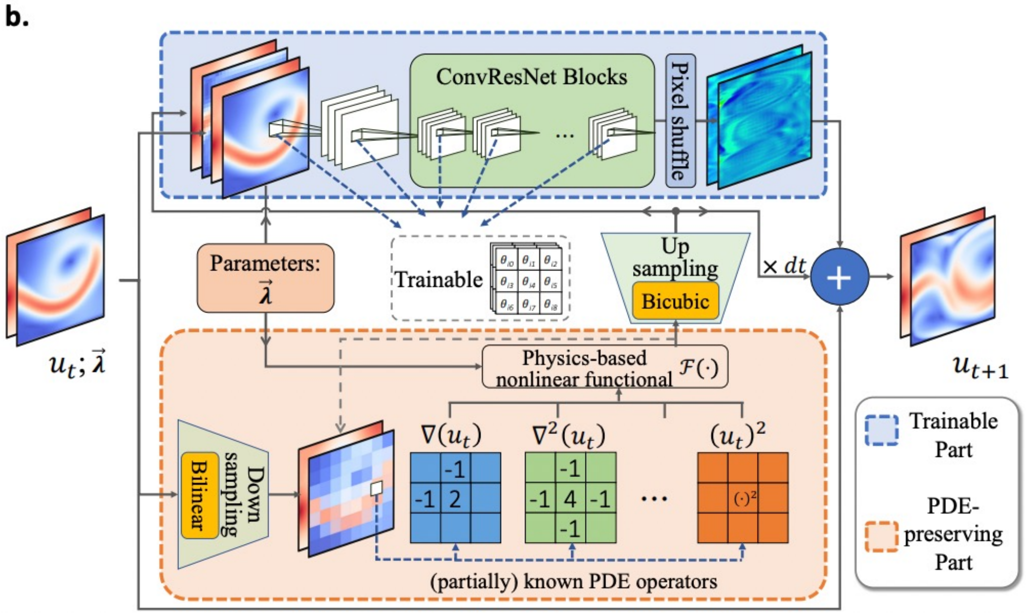


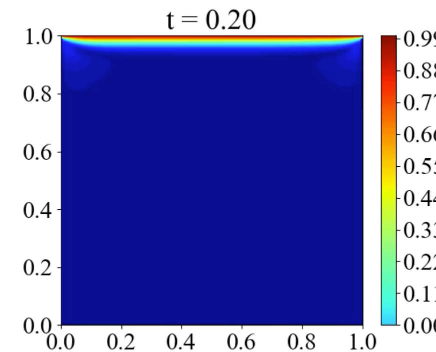
How many neurons in each layer?
How many layers?
What optimization scheme?
How much data?
What forward operation?
What non-linearity?
NN or other method?

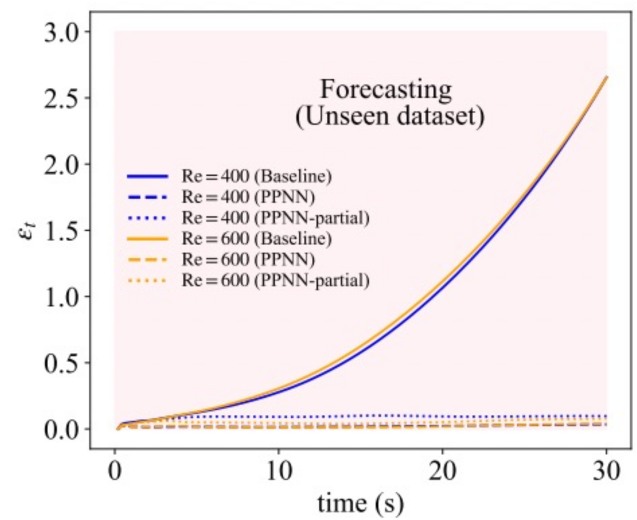
1. Intuition/Domain Knowledge
2. Exhaustive Search (Expensive!)
3. Random Search (Not efficient)
4. Bayesian Optimization (Gaussian Assumptions)
5. Reinforcement Learning
6. AutoML
7. …

Physics informed ML

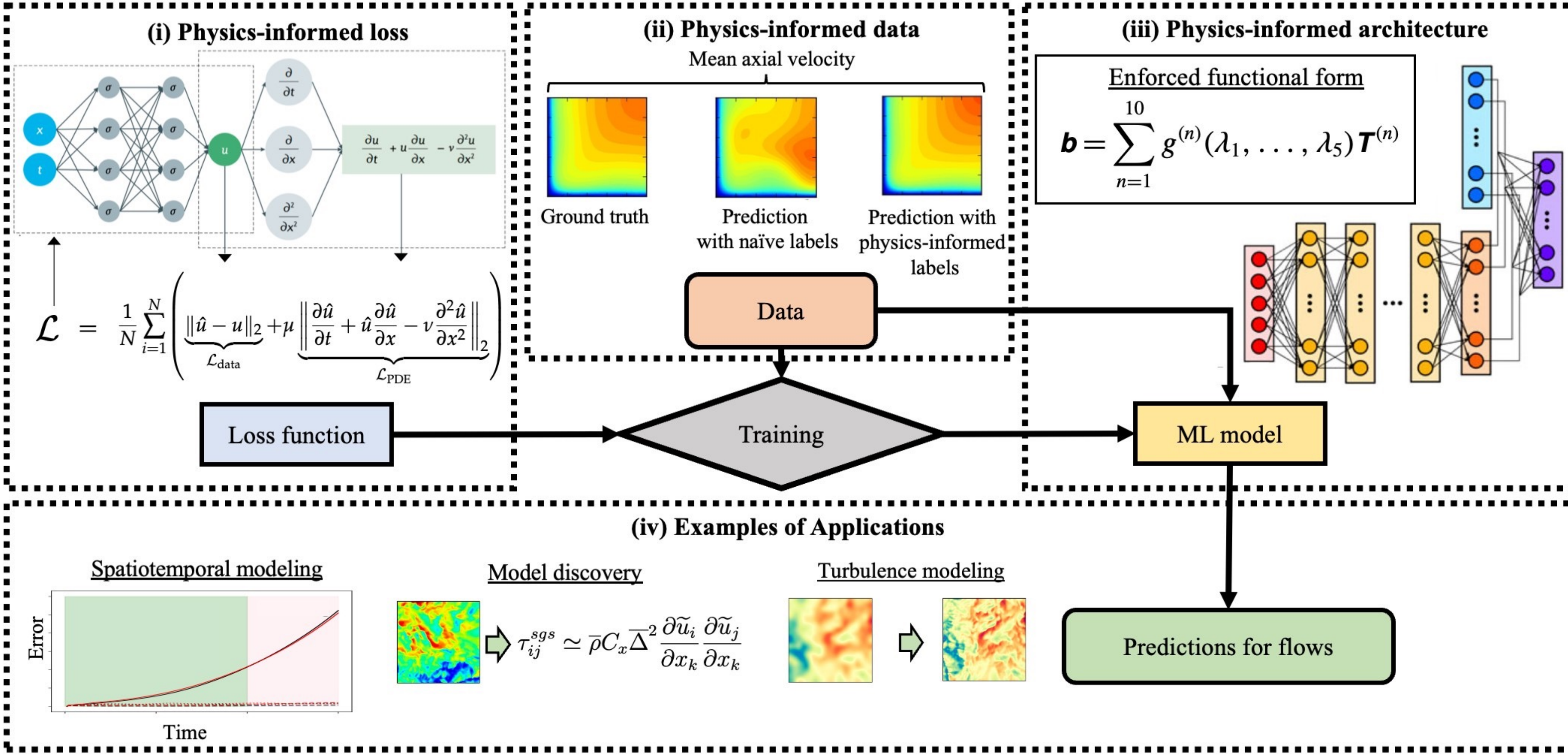
$$\frac{\partial \boldsymbol{u}}{\partial t} + \boldsymbol{u} \cdot \nabla \boldsymbol{u} = -\nabla p + \nu \nabla^2 \boldsymbol{u}, \quad t \in [0, T],$$
$$\nabla \cdot \boldsymbol{u} = 0,$$







Physics-informed ML in Fluid Mechanics



Conclusions

- This lecture: Applications, Opportunities, Challenges
  - When should I use ML?
    - Data
    - Forgiveable Errors
    - No better alternative
    - Low cost
  - How was ML done prior to current interest in ML?
  - How is ML research being done now in Wildfires?
  - What’s next?

Thank You