



Explainable AI and Semantic Web

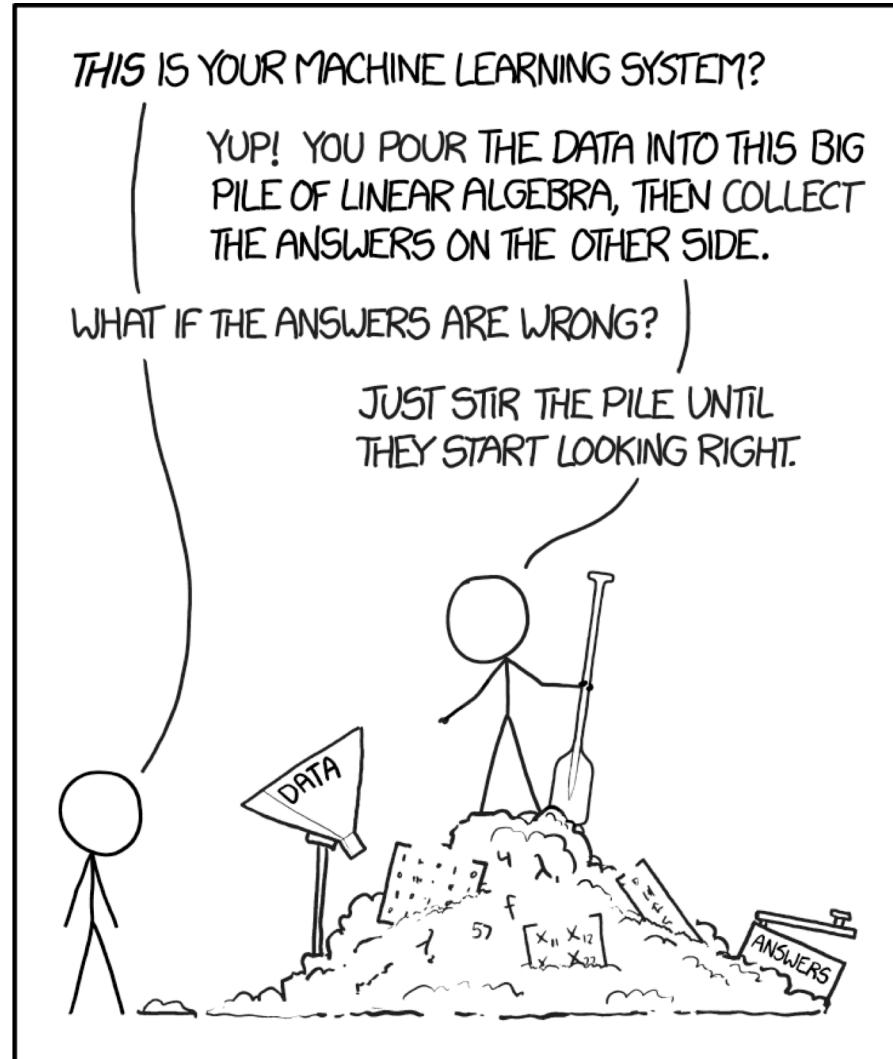
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Data Semantics Lab
Wright State University**

Outline



- Motivation
- What is explainable AI
- State of the art in different AI fields
- Limitation
- Scope of using Semantic web technologies

Our Machine Learning Model



https://imgs.xkcd.com/comics/machine_learning_2x.png

Consequences



<https://www.theverge.com/2018/3/21/17144260/healthcare-medicaid-algorithm-arkansas-cerebral-palsy>

- ❖ Artificial Intelligence is being used in Health Care, Judiciary Systems and has great impact on our life.

A thumbnail from The New York Times' website. It features a white background with a thin gray border. At the top right, it says "The New York Times". Below that, the word "Opinion" is written in a serif font. Underneath "Opinion", the text "OP-ED CONTRIBUTOR" appears. The main title "When a Computer Program Keeps You in Jail" is displayed in large, bold, black capital letters. Below the title, the author "By Rebecca Wexler" is mentioned. At the bottom, the date "June 13, 2017" is shown, along with social sharing icons for Facebook, Twitter, Email, and Print, and a count of "232" comments.

<http://nytimes.com/2017/06/13/opinion/how-computers-are-harming-criminal-justice.html>

Consequences



The Atlantic

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TECHNOLOGY

A Popular Algorithm Is No Better at Predicting Crimes Than Random People

The COMPAS tool is widely used to assess a defendant's risk of committing more crimes, but a new study puts its usefulness into perspective.

ED YONG JAN 17, 2018

<https://www.theatlantic.com/technology/archive/2018/01/equivant-compas-algorithm/550646/>

- ❖ The COMPAS tool is widely used to assess a defendant's risk of committing more crimes.
- ❖ But a new study puts its usefulness into perspective.

Two Petty Theft Arrests

VERNON PRATER

Prior Offenses

2 armed robberies, 1 attempted armed robbery

Subsequent Offenses

1 grand theft

LOW RISK

3

BRISHA BORDEN

Prior Offenses

4 juvenile misdemeanors

Subsequent Offenses

None

HIGH RISK

8

Borden was rated high risk for future crime after she and a friend took a kid's bike and scooter that were sitting outside. She did not reoffend.

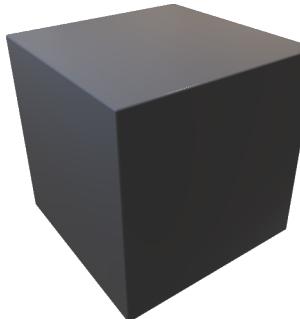




$$Y = f(X)$$

Minimize loss is the objective, non-linear transformation is the usual tool.

AI Model



Warehouse



Why it's a warehouse?

Why it's not a market?

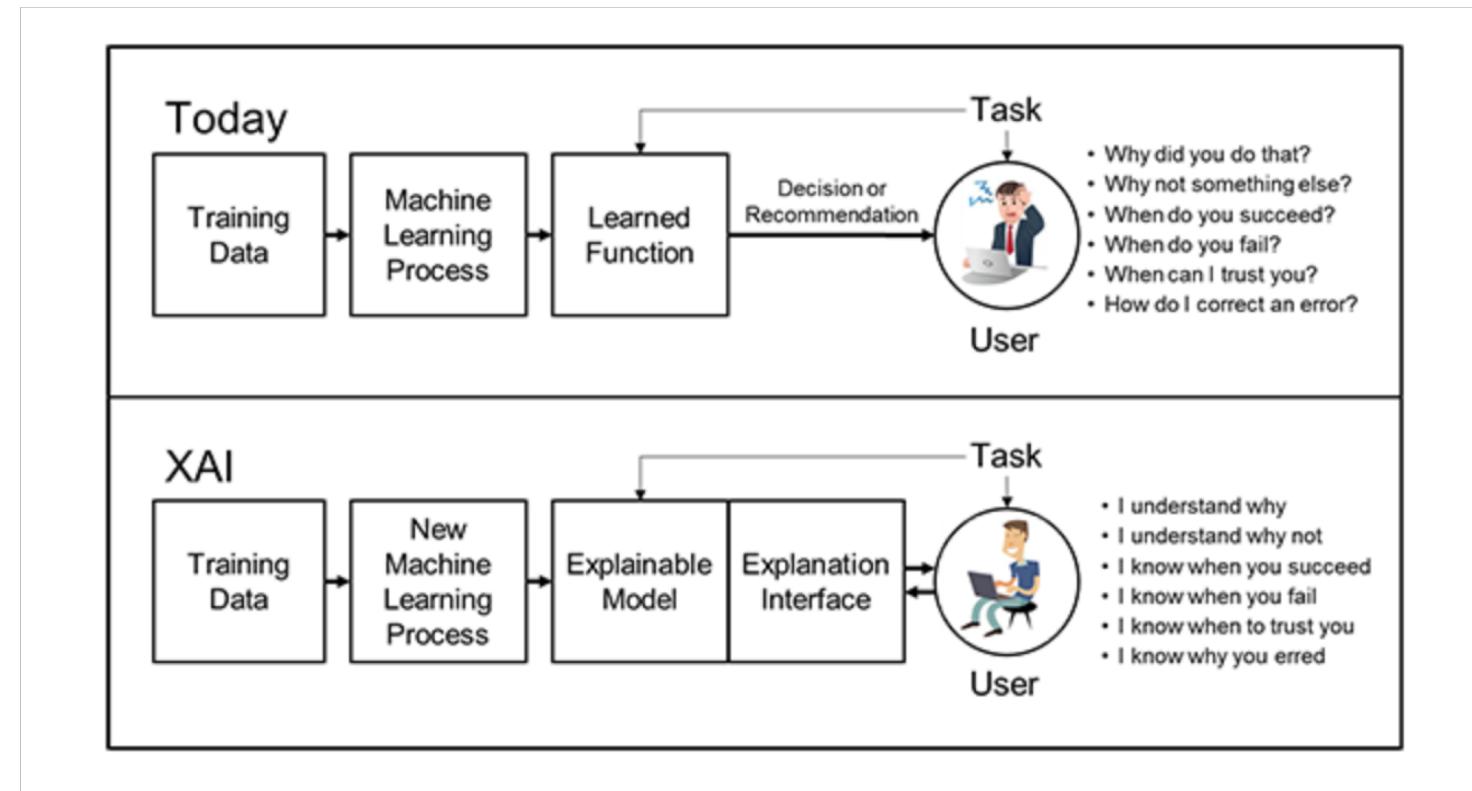
How it decided to call it warehouse?

When the transformation becomes too complicated we don't understand what is going inside.

We call it black box.

Explainable Artificial Intelligence

- We need to understand what is going on.
- Explainable AI (XAI) are the techniques which will help us to -
 - explain the decision
 - understand the decision and model
 - debug the decision



Explainable Artificial Intelligence

Mr. David Gunning, 2017, <https://www.darpa.mil/program/explainable-artificial-intelligence>

- No formal, technical, agreed upon definition!
- Comprehensive philosophical overview out of scope of the tutorial
- Explainability is an ill-defined term! [Lipton 2016]
- Different level of people need different type of explainability!
- Not limited to machine learning! [Lipton 2016, TomseL et al. 2018, Rudin 2018]

Ontology Design pattern for explanation

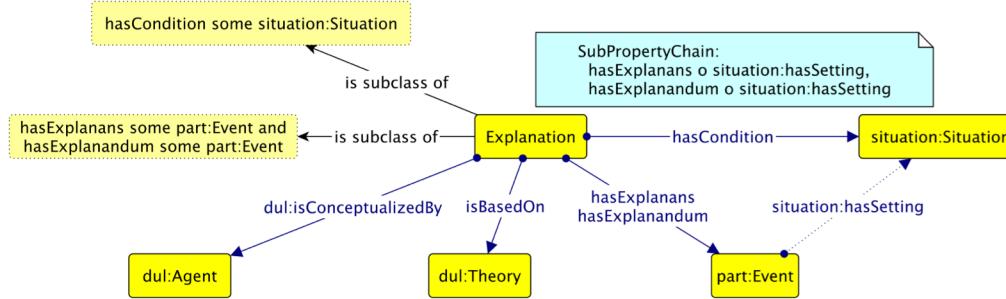


Figure 2: The Explanation Ontology Design Pattern.

[Ilaria 2015]

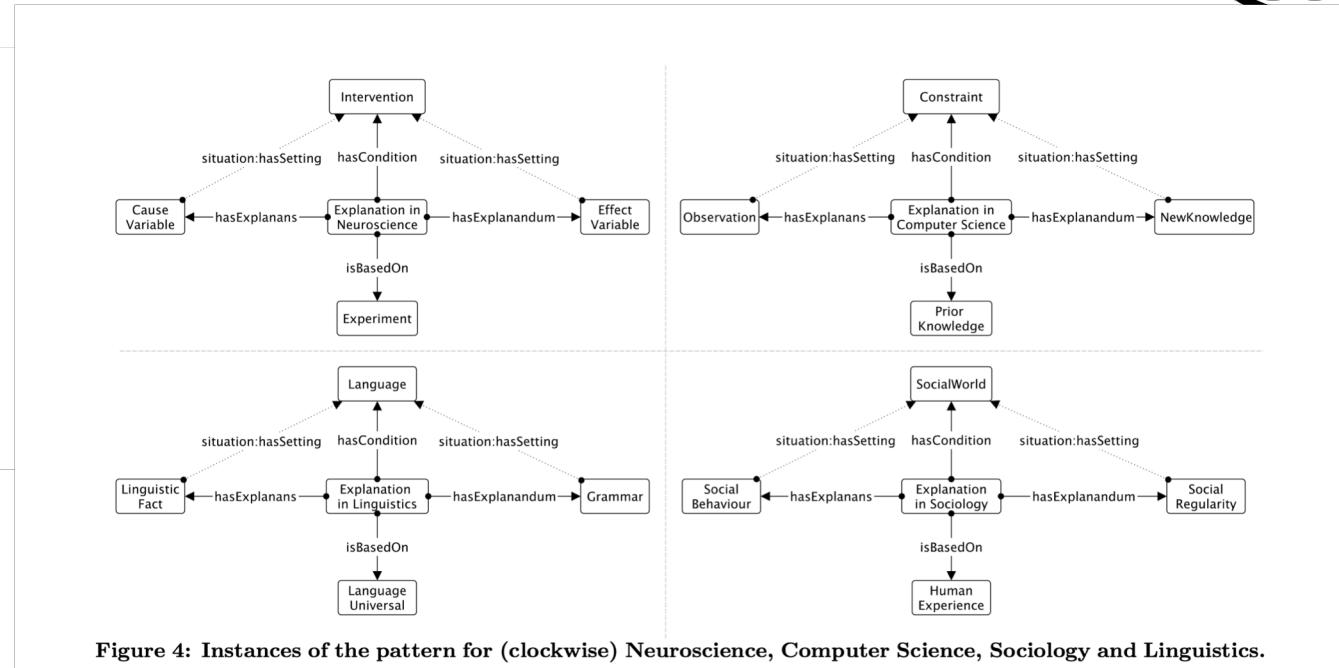


Figure 4: Instances of the pattern for (clockwise) Neuroscience, Computer Science, Sociology and Linguistics.

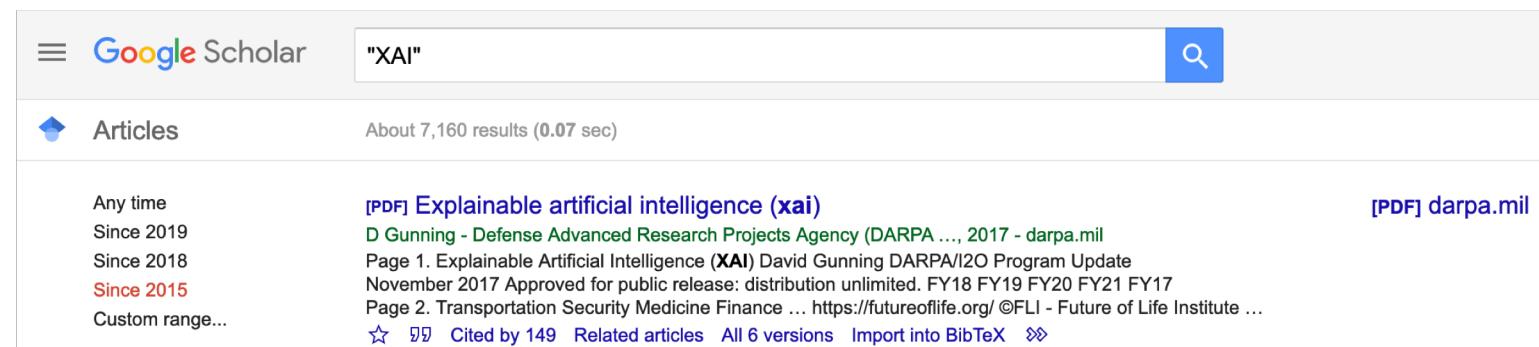
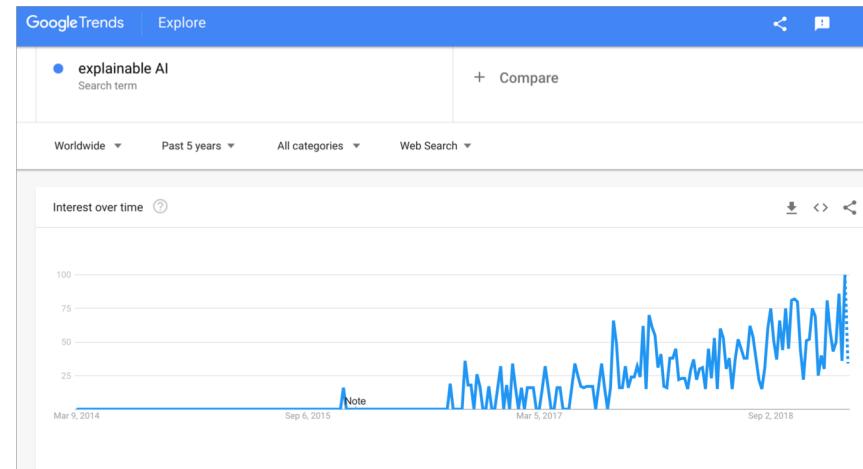
Explanation differs by field !!

Explainable AI is a branch of AI which help to get explanation from the AI model.

Explanation is the ability of the model to satisfy users **understandability of the **decision** and **model**.**

Explainable AI

- Moving from the definition we need to explain the AI models.
- Trend on google shows large interest for this.
- Researchers are also working hard to find ways.
- More than 7000 papers related to XAI since 2015.



Options for Explanation



- Before Building Model

Explanation

- During Building Model

Explanation

- After Building Model

Explanation

Before Building Model



- Feature Visualization¹
- Exploratory data analysis²
 - Some features may be redundant
 - Some features may not help the model
- Correlation can be used to identify redundant features. [The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Trevor Hastie Robert Tibshirani Jerome Friedman]

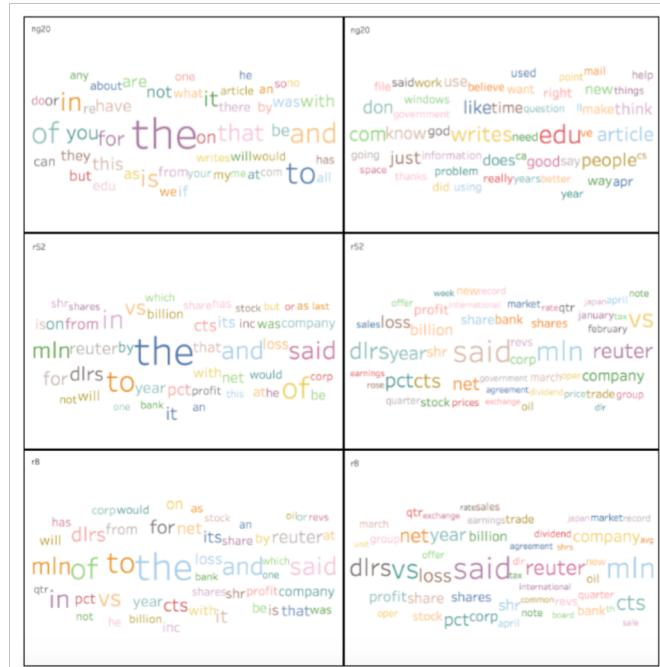
How much this help for explanation?

[1,2]
[Viégas and Wattenberg '07]
[Maaten et al. '08]
[Amershi et al. '09]
[Patel et al. '10]
[Varshney et al. '12]
[Tukey 77]

Feature Visualization & Exploratory data analysis



- Word Cloud for 20 news group dataset for different classes.
- Helps to get idea for which class has which type of texts.



<http://qwone.com/~jason/20Newsgroups/>

How much this help for explanation?

- Give some idea about the dataset.
- Different classifier work differently, so not giving explanation about the model.
- If features are not understandable (numeric) this only helps to get cluster of group, but does not help for human understanding of the classifier decision or model.

- Before Building Model

Explanation

- During Building Model

Explanation

- After Building Model

Explanation

Not satisfying
us, let's go to
next step

During Building Model



- **Choosing interpretable model**
 - Common belief that some models are explainable.
 - Rule Based model
 - KNN
 - Linear Regression
 - Decision tree
 - Are they really interpretable?



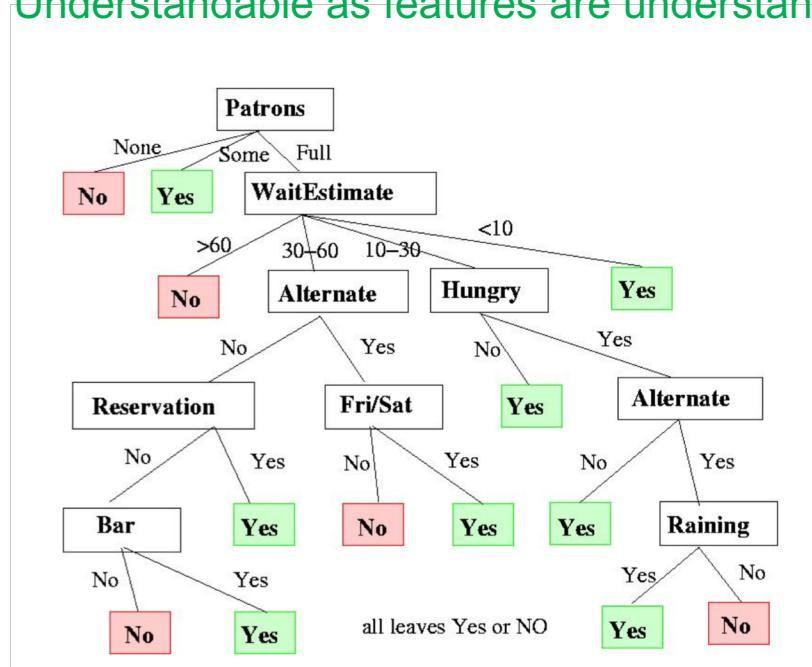
Choosing interpretable model

- Develop rule based model which has theoretical underpinning to the solution.
 - [Breiman, Friedman, Stone, Olshen 84]
 - [Rivest 87]
 - [Muggleton and De Raedt 94]
 - [Wang and Rudin 15]
- Using rule set user can trace how the solution is being made.
- For large systems making rule set is not feasible.
 - Face recognition system with thousand of features!!!!
- For some systems making rule set is not even practical.
 - Music classifier where input comes as waveform.

During Building Model

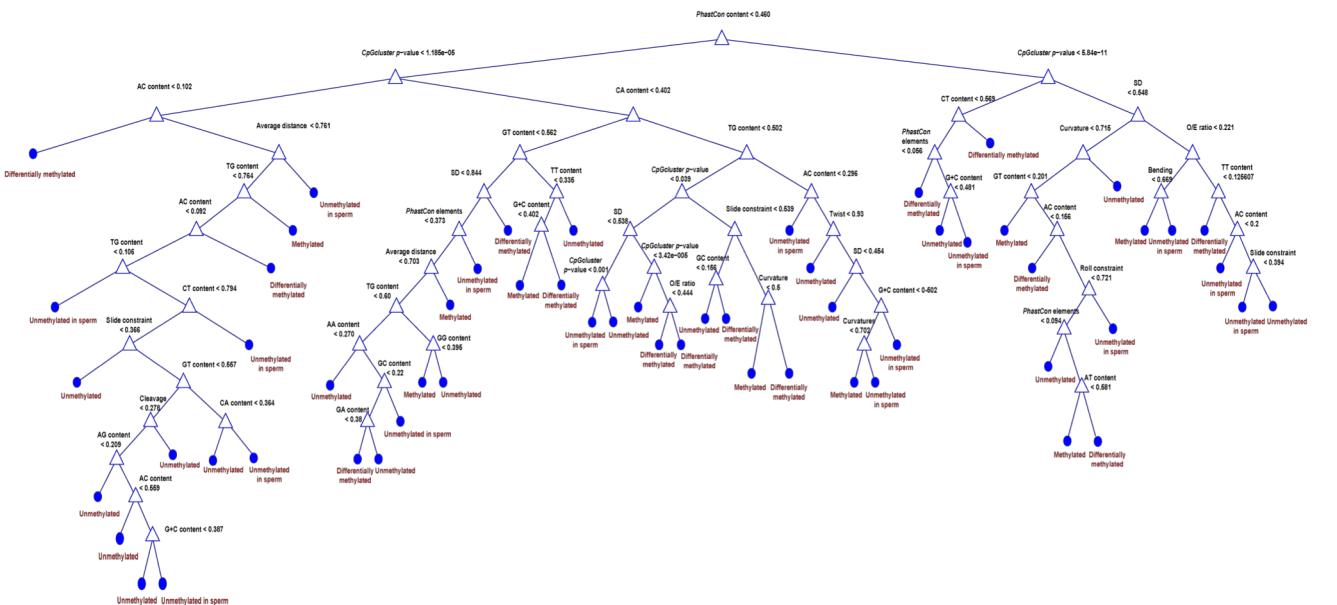
Decision Tree : Example

- Problem to wait or not for a table at a restaurant?
- Understandable as features are understandable.



<http://www.cs.bham.ac.uk/~mmk/Teaching/AI/I3>

- Problem is to predict the class from four CGI methylation classes.
- Hard to understand and even hard to visualize.



[Previti 2009]

During Building Model



- Rule Based model
- KNN
- Linear Regression
- Decision tree

Rule based model are not scalable.

Others are interpretable as long as the model is small.

- Before Building Model

Explanation

Not satisfying
us, let's go to
next step

- During Building Model

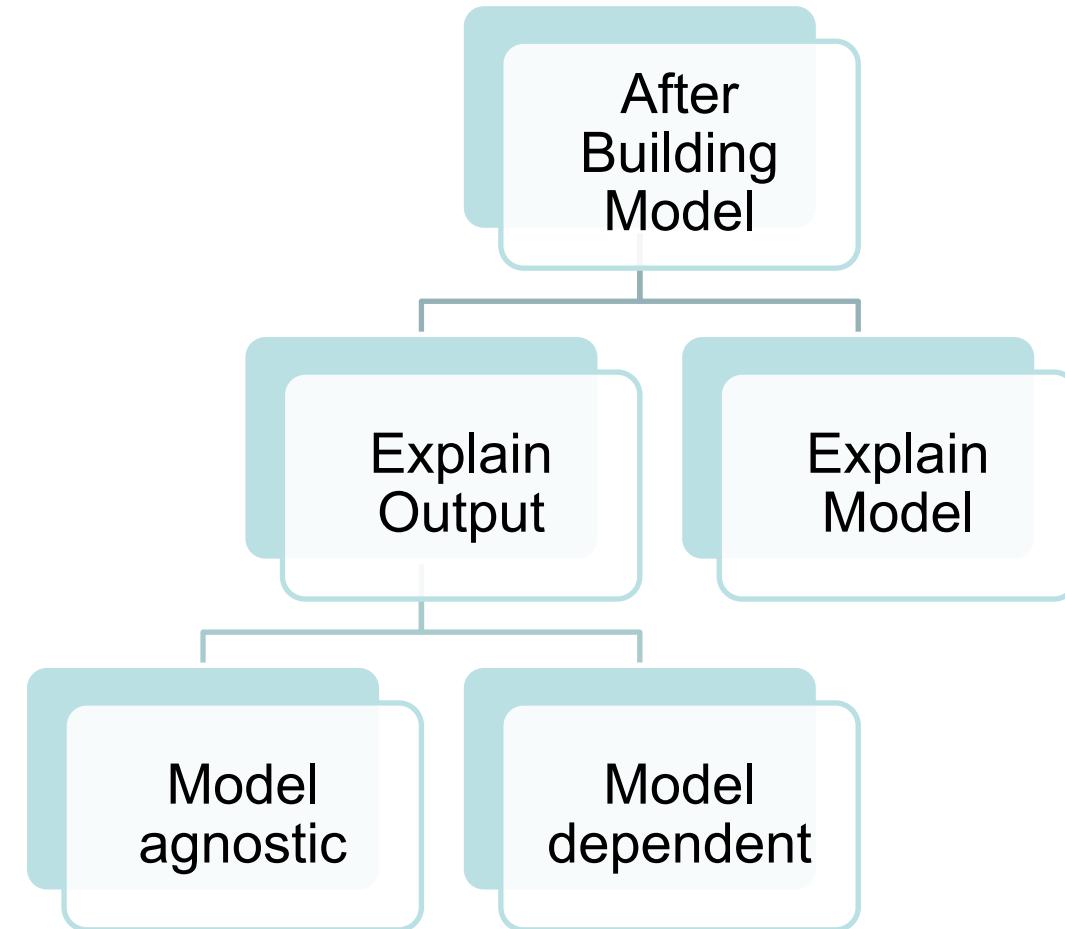
Explanation

Not satisfying
us, let's go to
next step

- After Building Model

Explanation

After Building Model

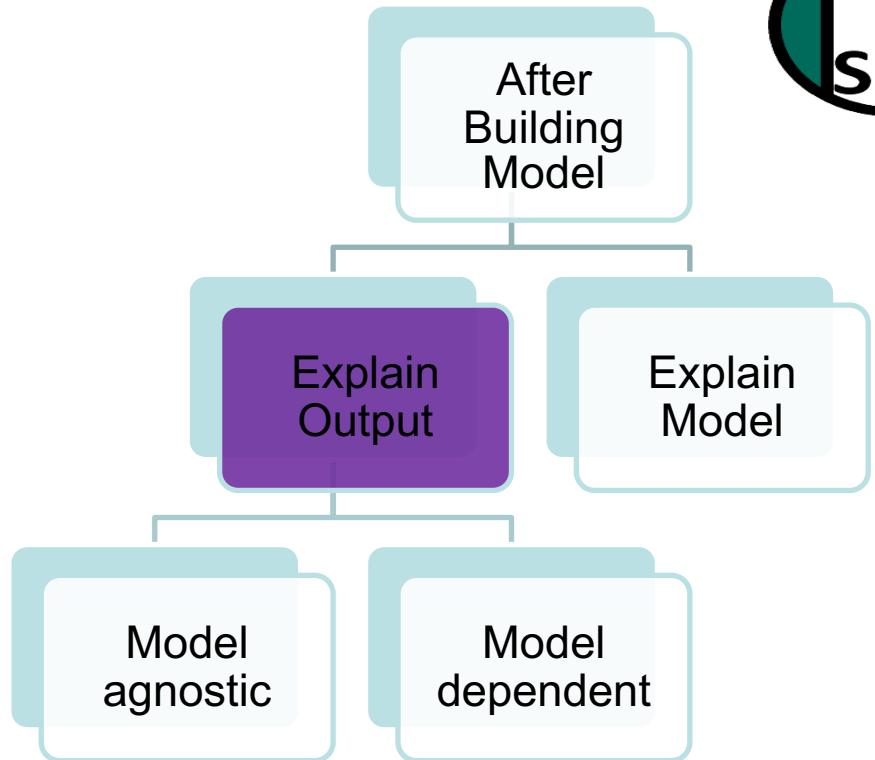


Explain Output



Large class of AI models

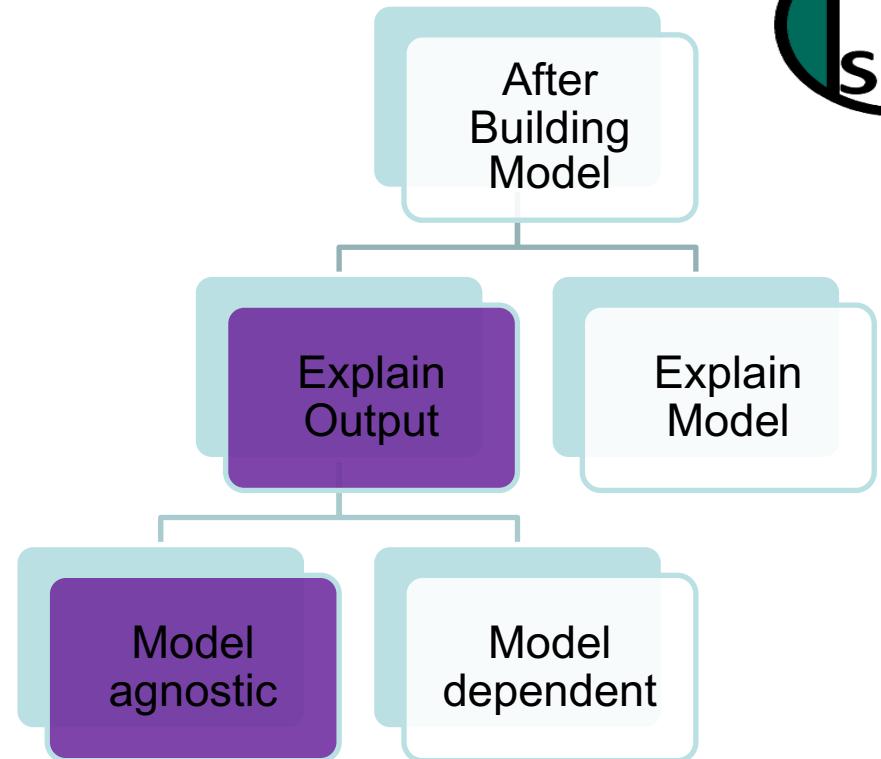
- Deep Neural Network
 - Convolutional Neural Network
 - LSTM
 - Recurrent Neural Network
 - SVM
-
- Some explanation techniques are model dependent and some are not. [Riccardo, 2018]



Model Agnostic



- These techniques try to explain any AI model.
- $y = f(x)$
- f is any AI model, it can be
 - Neural Network
 - Support Vector Machine
 - Random Forest
 -





LIME : Local Interpretable Model-Agnostic Explanations¹ Anchors: High-Precision Model-Agnostic Explanations²

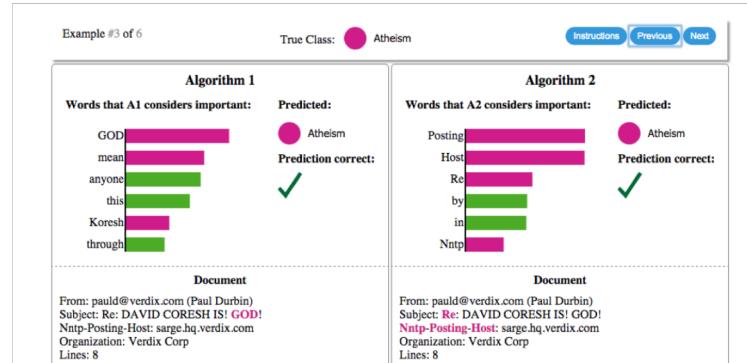


Figure 2: Explaining individual predictions of competing classifiers trying to determine if a document is about “Christianity” or “Atheism”. The bar chart represents the importance given to the most relevant words, also highlighted in the text. Color indicates which class the word contributes to (green for “Christianity”, magenta for “Atheism”).

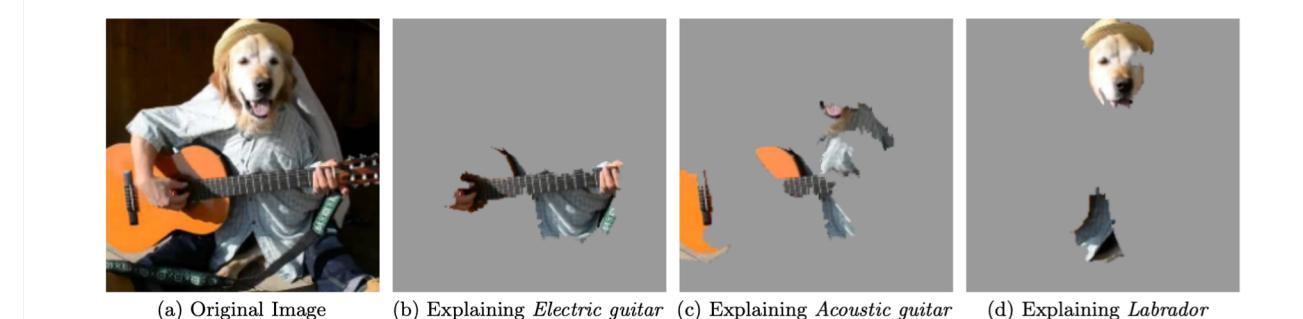
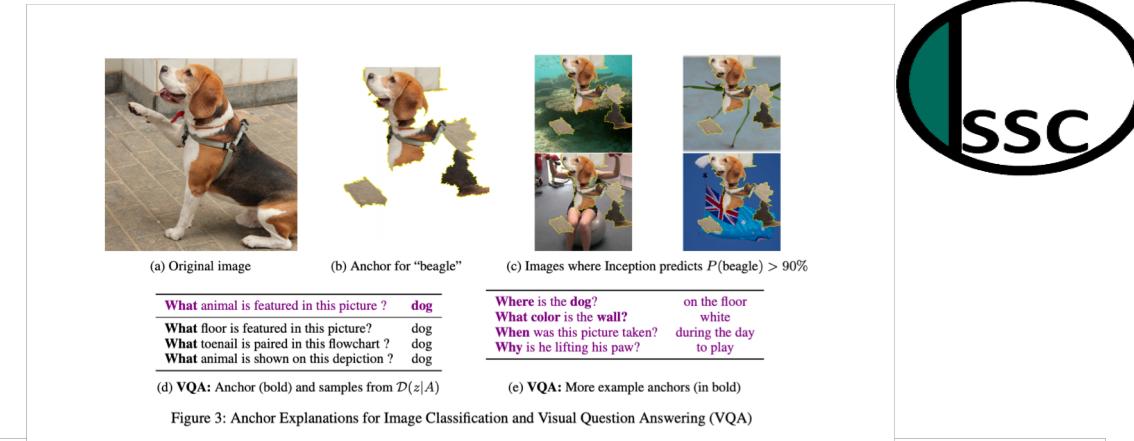


Figure 4: Explaining an image classification prediction made by Google’s Inception neural network. The top 3 classes predicted are “Electric Guitar” ($p = 0.32$), “Acoustic guitar” ($p = 0.24$) and “Labrador” ($p = 0.21$)

- Explain models by presenting representative individual predictions
- Perturb the input data around the prediction locally

¹[Ribeiro 2016], ²[Ribeiro 2018]

Model Agnostic



- **LORE : LOcal Rule-based Explanations** [Guidotti, 2018]
 - Uses a genetic algorithm approach to generate a decision tree as interpretable classifier
 - Explanation consists in a rule derived from the decision tree classifier.
 - LORE also returns a set of counterfactual rules, suggesting the changes in the instance's features of x that may lead to a different outcome.

$$r = \{ \{ \text{credit_amount} \leq 836, \text{housing} = \text{own}, \text{other_debtors} = \text{none}, \text{credit_history} = \text{critical account} \} \rightarrow \text{decision} = 0 \}$$
$$\Phi = \{ \{ \text{credit_amount} > 836, \text{housing} = \text{own}, \text{other_debtors} = \text{none}, \text{credit_history} = \text{critical account} \} \rightarrow \text{decision} = 1, \{ \{ \text{credit_amount} \leq 836, \text{housing} = \text{own}, \text{other_debtors} = \text{none}, \text{credit_history} = \text{all paid back} \} \rightarrow \text{decision} = 1 \} \}$$



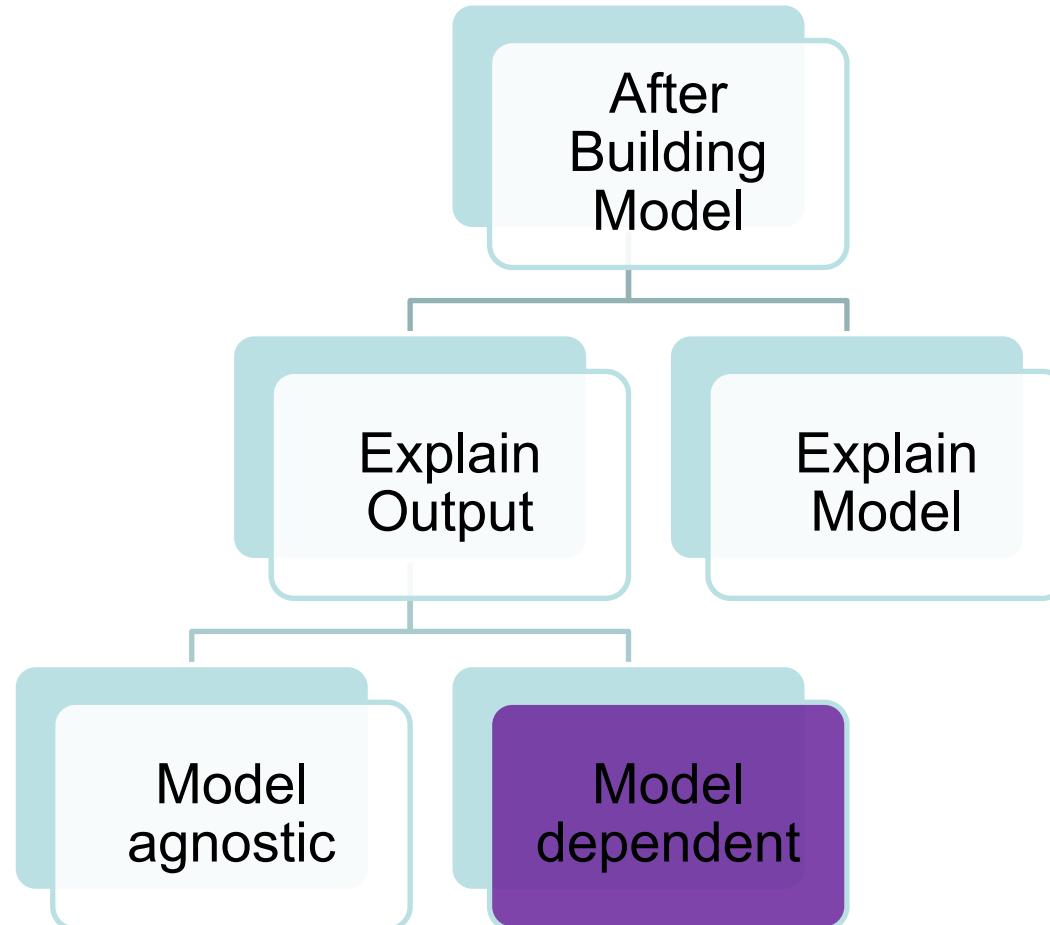
Limitation

- Explanation are not stable.
- Same model m, same input x can generate different explanation.
- Explanation only faithful locally.
- If input x come from different distribution explanation are terrible.

After Building Model



- Model dependent explanations are mostly for neural networks and its variants.
- Mainly two approaches are used.
 1. **Investigate the hidden layers**
 2. **Build another model to create explanation**



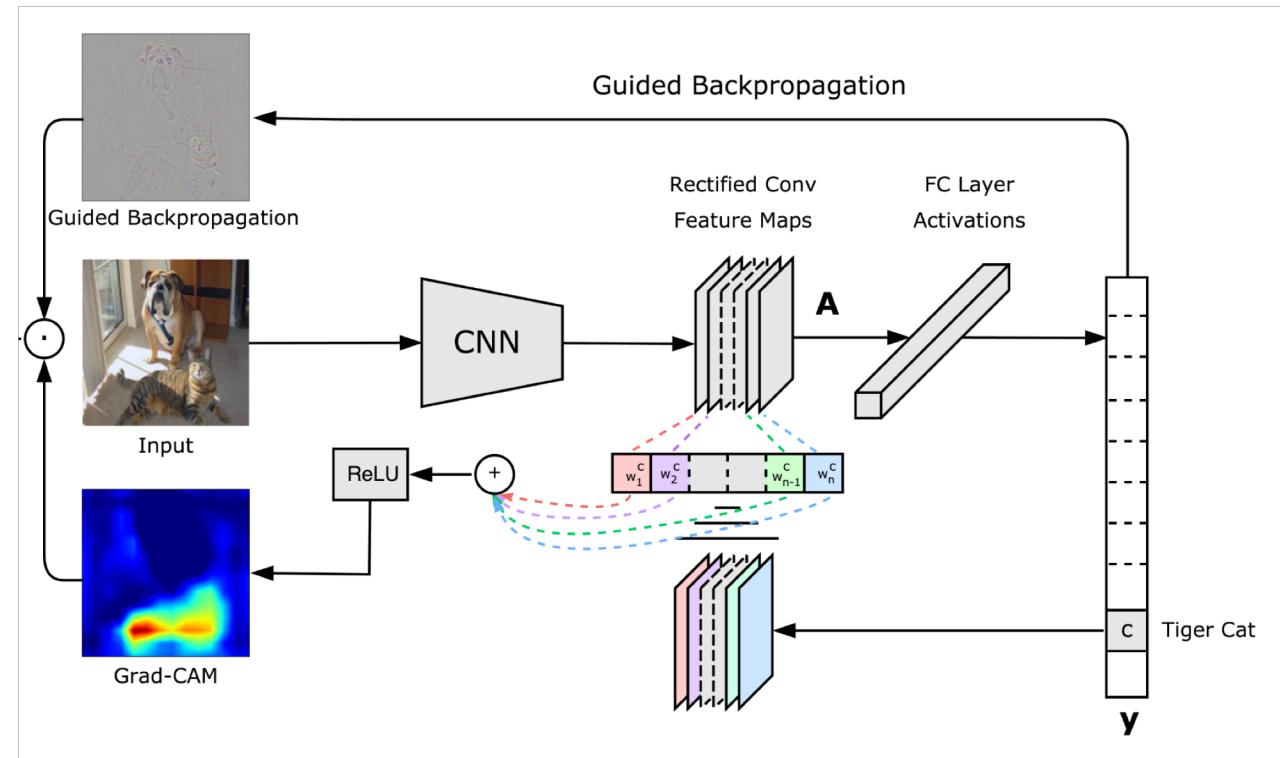
Model Dependent

Investigate the hidden layers

Visualizing the regions of the input that are "important" for predictions.

Common Strategy:

1. Backpropagate the output/loss/gradient to the input layer.
2. Compares the activation of each neuron to its 'reference activation'
3. Show the difference.

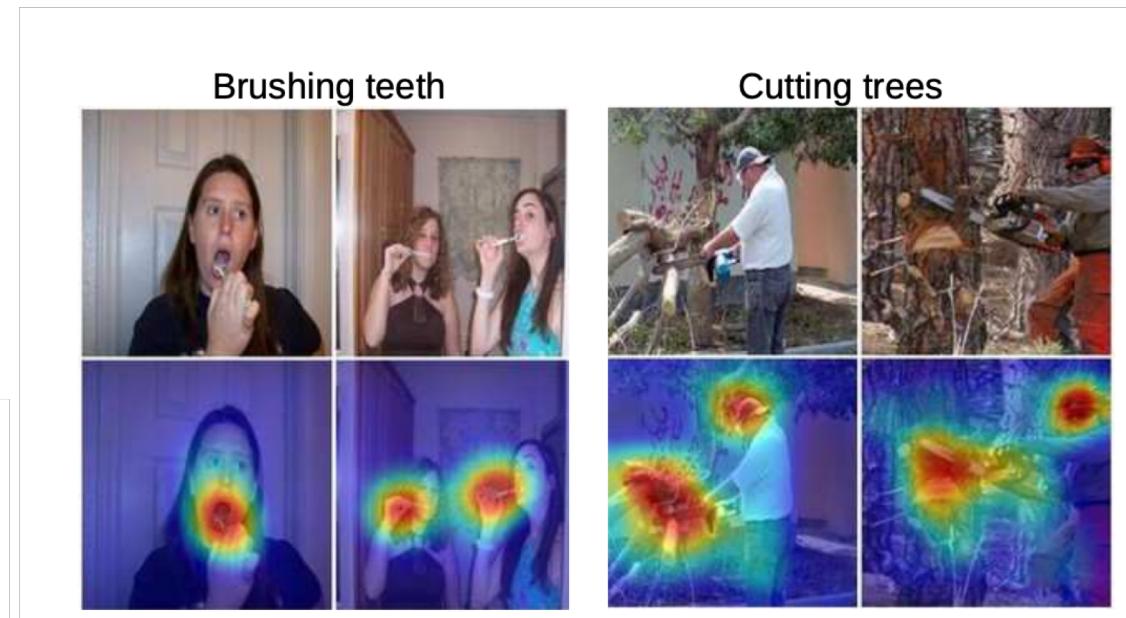
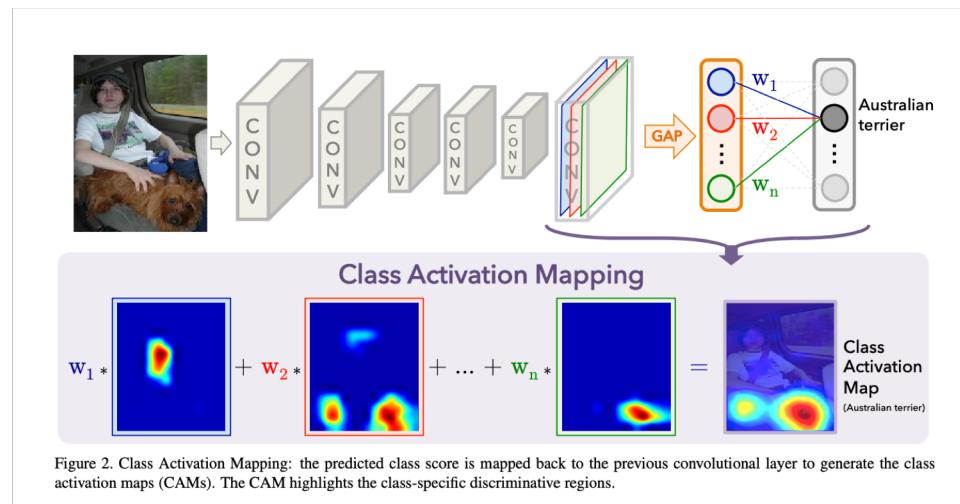


Ramprasaath R. Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, Dhruv Batra "Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization", <https://arxiv.org/abs/1610.02391>

Model Dependent

Investigate the hidden layers

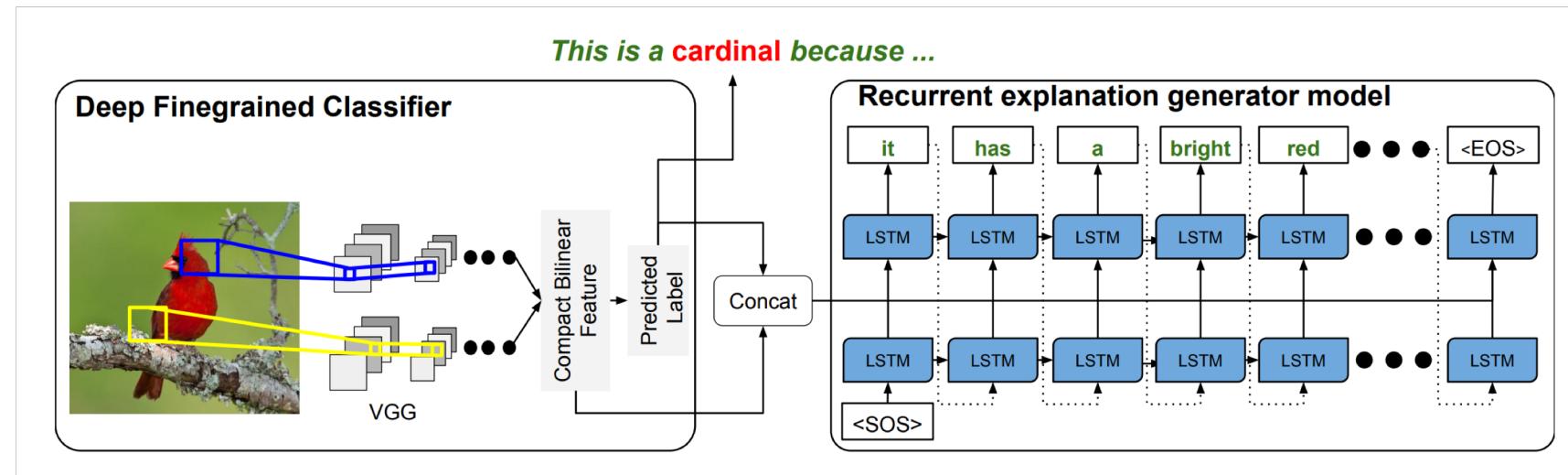
Showing important part of the input which contributes more to the class decision.



Bolei Zhou, Aditya Khosla, Agata Lapedriza, Aude Oliva, Antonio Torralba,
Learning Deep Features for Discriminative Localization, <https://arxiv.org/abs/1512.04150>

Build another model to create explanation

Train a black box and then **again train another black box** to produce explanation!!



Visual explanations [Hendricks et al. '16]

What will happen if the explanation module produces wrong explanation ??



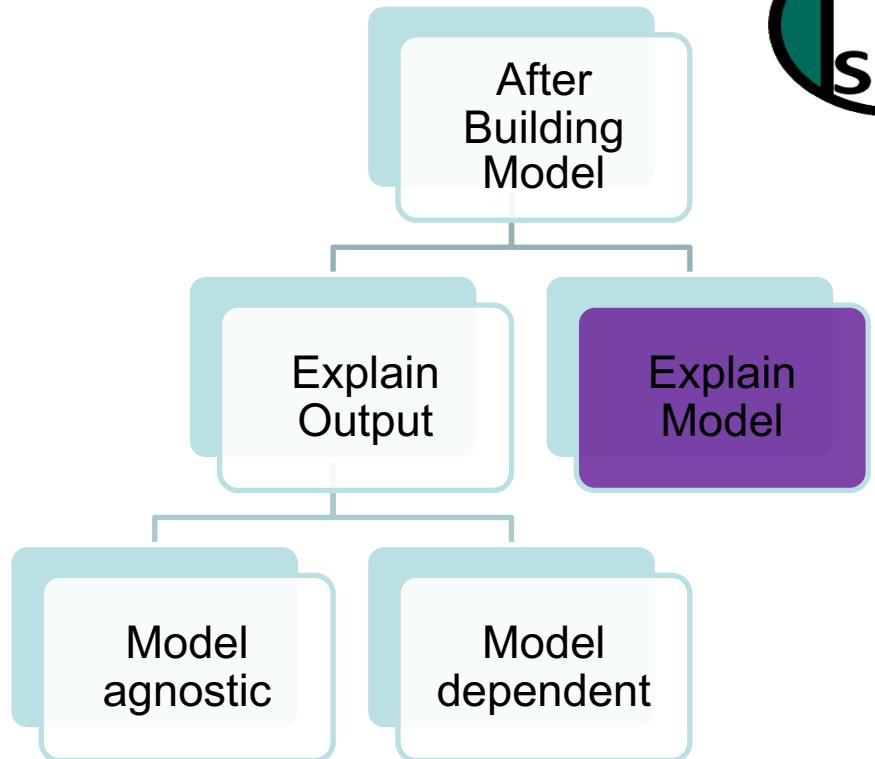
Limitation

- Some-times explanation are hard to understand.
- Single bit change in the input (even if the if input is large) may give different explanation.
- Newly created explanation module may give wrong answers.

Model Explanation



- Need to understand how the model is producing output.
- Is the model generalized enough so it will not be fooled?
(Adversarial attack) [Chakraborty, 2018]
- Mainly two approaches:
 - Rule extraction from neural network.
 - Looking the hidden layers





Rule extraction from neural network.

[Sebastian Thrun, 1995]

[Tameru Hailesilassie, 2016]

[Mark W. Craven, 1996]

- Create rule/decision tree from trained neural network.
- Works for small number of features
- and where the features are understandable.

Model Explanation



- **Rule extraction from neural network**
 - Showing rule set for classifying electronics out of 4 class ('Space', 'Medicine', 'Electronics' and 'Cryptography' from the 20-newsgroups dataset for text classification).
 - If n features then at-least 2^n possible rules. !!
 - Not scalable for large models.
 - Is it easy to understand the rules?

```
if (just = -1) and (use = 1) ==> electronics (24/24)
elif (circuit = 1) ==> electronics (32/32)
elif (just = -1) and (don = 1) ==> electronics (11/11)
elif (people = 0) and (used = 1) and (key = 0) and (don = 0) and (use = 0) and (edu = 0) and (medication = 0) and (concept = 0) and (did = 0) ==> electronics (36/43)
elif (electronics = 1) ==> electronics (17/18)
elif (battery = 1) ==> electronics (23/23)
elif (radio = 1) and (shack = 1) ==> electronics (9/9)
elif (people = 0) and (thanks = 1) and (advance = 1) ==> electronics (12/14)
elif (signal = 1) ==> electronics (13/15)
elif (people = 0) and (company = 1) and (just = 0) ==> electronics (13/18)
elif (pc = 1) ==> electronics (16/19)
elif (people = 0) and (use = 1) and (just = 0) and (good = 0) and (clipper = 0) and (probably = 0) and (center = 0) and (unless = 0) and (18084tm = 0) and (algorithms = 0) ==> electronics (29/33)
elif (appreciated = 1) and (time = 0) ==> electronics (11/16)
elif (voltage = 1) ==> electronics (8/8)
elif (program = -1) ==> electronics (10/15)
else: others (1134/1281)
```

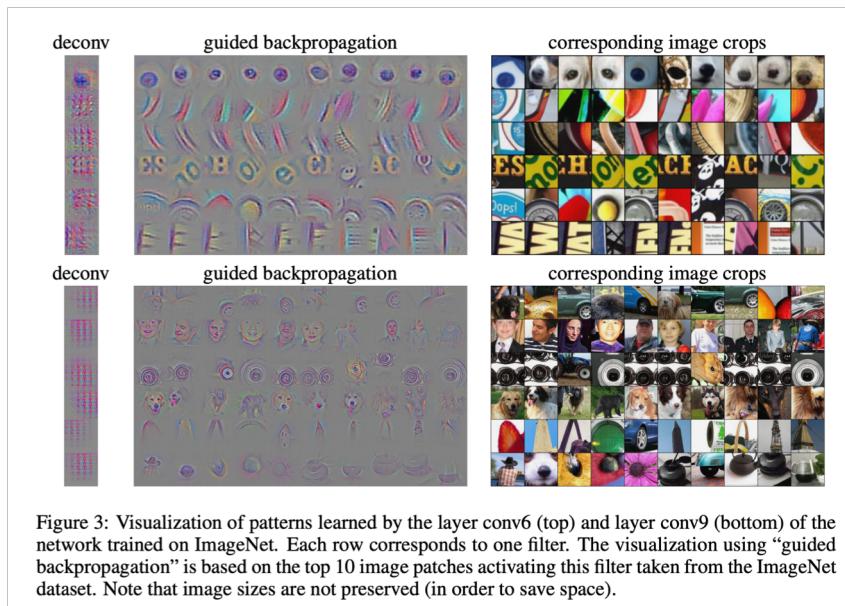
Figure 2: Set of if-then-else rules that explain the predictions of the neural network for the 'electronics' class when using mutual information feature selection. Here the discrete test value 1 means a positive correlation between a feature value (which we can approximate to relative frequency due to the use of TF-IDF vectors) and the probability of the class, -1 means a negative correlation, and 0 shows an absence of a feature. The values (a/b) mean that a of b instances covered by the rule are correct. The rules with lower values of a/b are less trustworthy, and the rules with lower value of b, especially in the first few conditions, are less generalized.

[Sushil 2018]

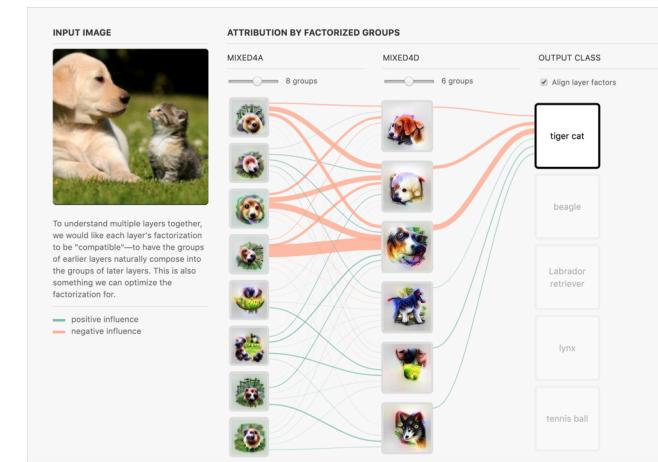
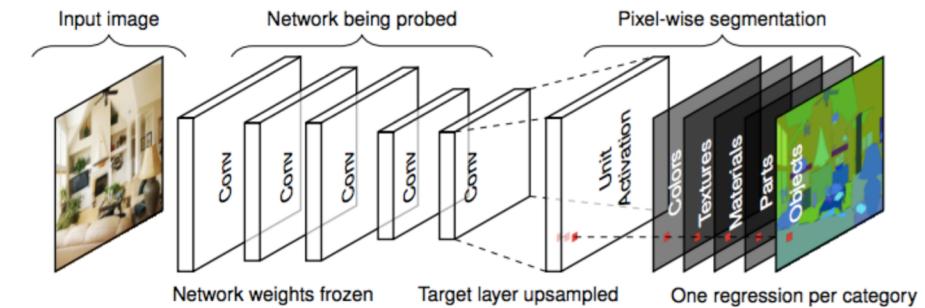
Model Explanation

Looking the hidden layers

- Visualize the hidden conv layers
- This approach mostly suited for image classification.
- We get some sense of what is going inside.
- Some times the pictures we get from hidden layers are not understandable.



[Springenberg, 2015]



<https://distill.pub/2019/activation-atlas/>

Limitation

- Ruleset are hard to understand for big models.
- Visualization only helps for image classification
- Parts of the pictures don't always make understandable object.
- Human understands hierarchical relation easily but, no relationship between the objects are maintained.



- Before Building Model

Explanation

**Not satisfying
us, let's go to
next step**

- During Building Model

Explanation

**Not satisfying
us, let's go to
next step**

- After Building Model

Explanation

**Somewhat
satisfying but not
fully.**

- After failing to understand the explanation using XAI techniques what can we do?
 - More Research using statistics, deep learning, linear algebra?
 - Can we use semantic web techniques?

Using Semantic Web Techniques



- Semantic web has millions of structured triples.
- And those triples are related to each other.
- Using those related triples may enhance our understandability on what's going inside.

DBpedia Browse using ▾ Formats ▾ Faceted Browser Sparql Endpoint

About: Warehouse

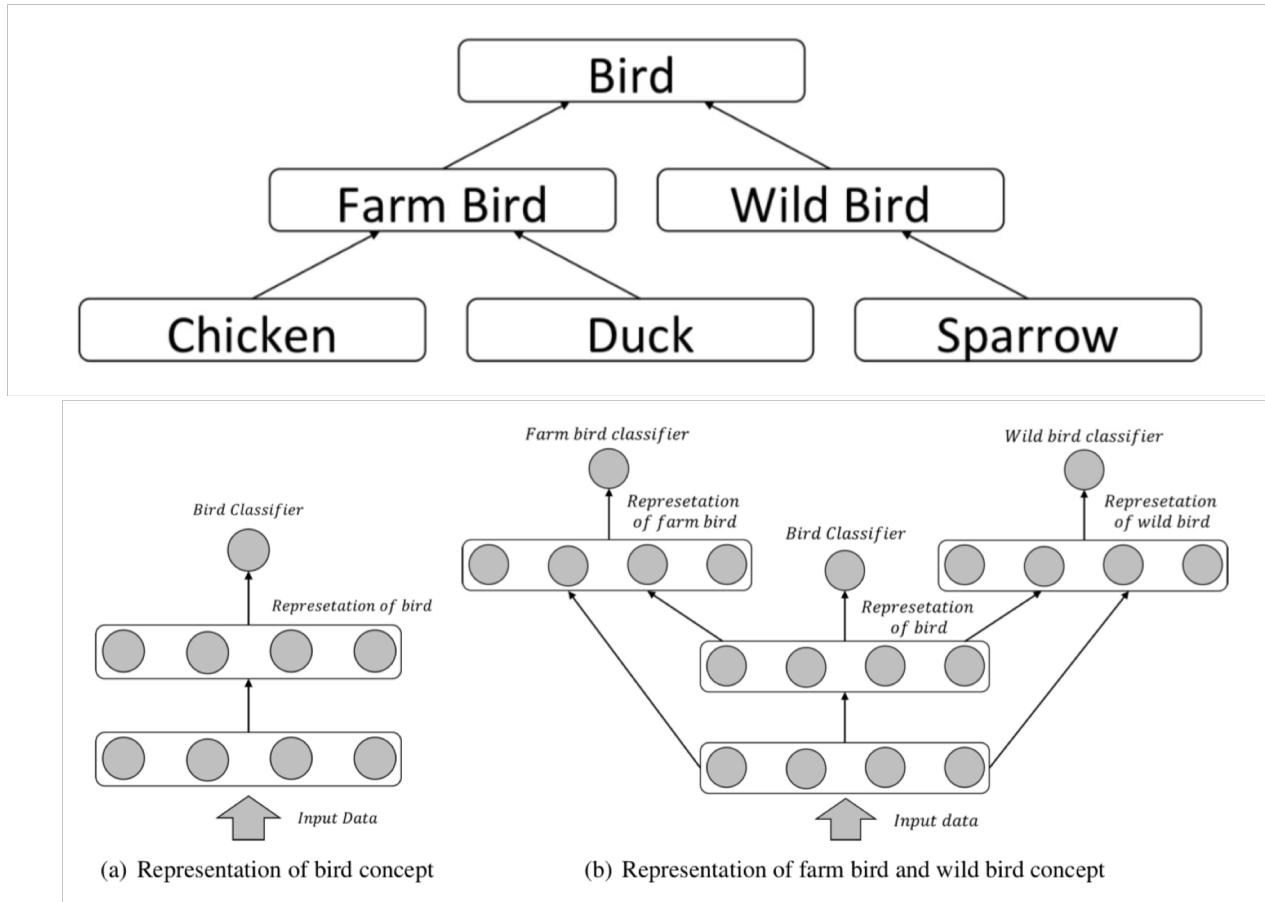
An Entity of Type : [building](#), from Named Graph : [http://dbpedia.org](#), within Data Space : [dbpedia.org](#)

A warehouse is a commercial building for storage of goods. Warehouses are used by manufacturers, importers, exporters, wholesalers, transport businesses, customs, etc. They are usually large plain buildings in industrial areas of cities, towns and villages.

Property	Value
dbo:abstract	<ul style="list-style-type: none">A warehouse is a commercial building for storage of goods. Warehouses are used by manufacturers, importers, exporters, wholesalers, transport businesses, customs, etc. They are usually large plain buildings in industrial areas of cities, towns and villages. They usually have loading docks to load and unload goods from trucks. Sometimes warehouses are designed for the loading and unloading of goods directly from railways, airports, or seaports. They often have cranes and forklifts for moving goods, which are usually placed on ISO standard pallets loaded into pallet racks. Stored goods can include any raw materials, packing materials, spare parts, components, or finished goods associated with agriculture, manufacturing and production. In Indian English a warehouse may be referred to as a godown. (en)
dbo:thumbnail	<ul style="list-style-type: none">wiki-commons:Special:FilePath/Automatisches_Kleinteilelager.jpg?width=300
dbo:wikiPageExternalLink	<ul style="list-style-type: none">http://logisticsbureau.com/warehouse-analytics-for-astute-logisticians/http://www.yesdee.com/ysdbook.php?ysde=409&ys=0-64-56
dbo:wikiPageID	<ul style="list-style-type: none">549146 (xsd:integer)

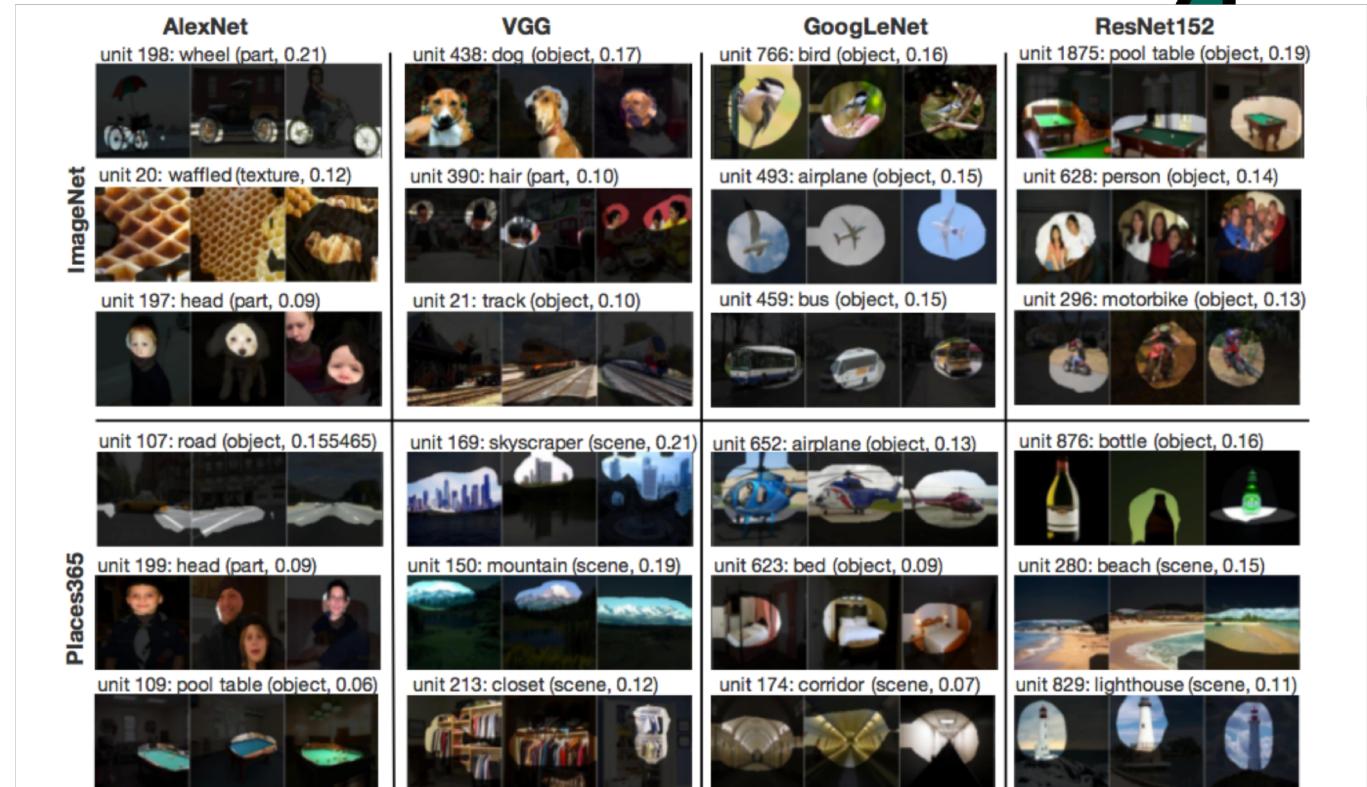
Using Semantics

- Set the goal of classification as **hierarchical classification**. [Wang 2015]
 - Easily understandable by human.
 - But the problem is optimization gets even harder.



Using Semantics

- [Zhou 2018] is showing hidden layers objects and corresponding labels.
- Give better intuition of what is going on inside, but it requires large semantic annotations of the objects.
- Currently one object is not related with other objects.
- **Need collaboration between semantic web community and deep learning community.**



[Zhou 2018]



Using semantics

Using semantics

- Before Building Model

- During Building Model

- After Building Model

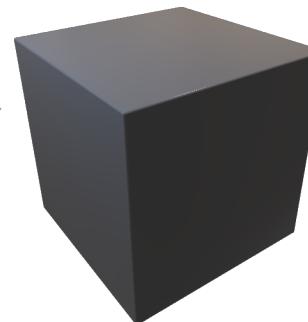


Not satisfying us,
let's go to next step

Optimization gets
more complicated

Enhances
explanation

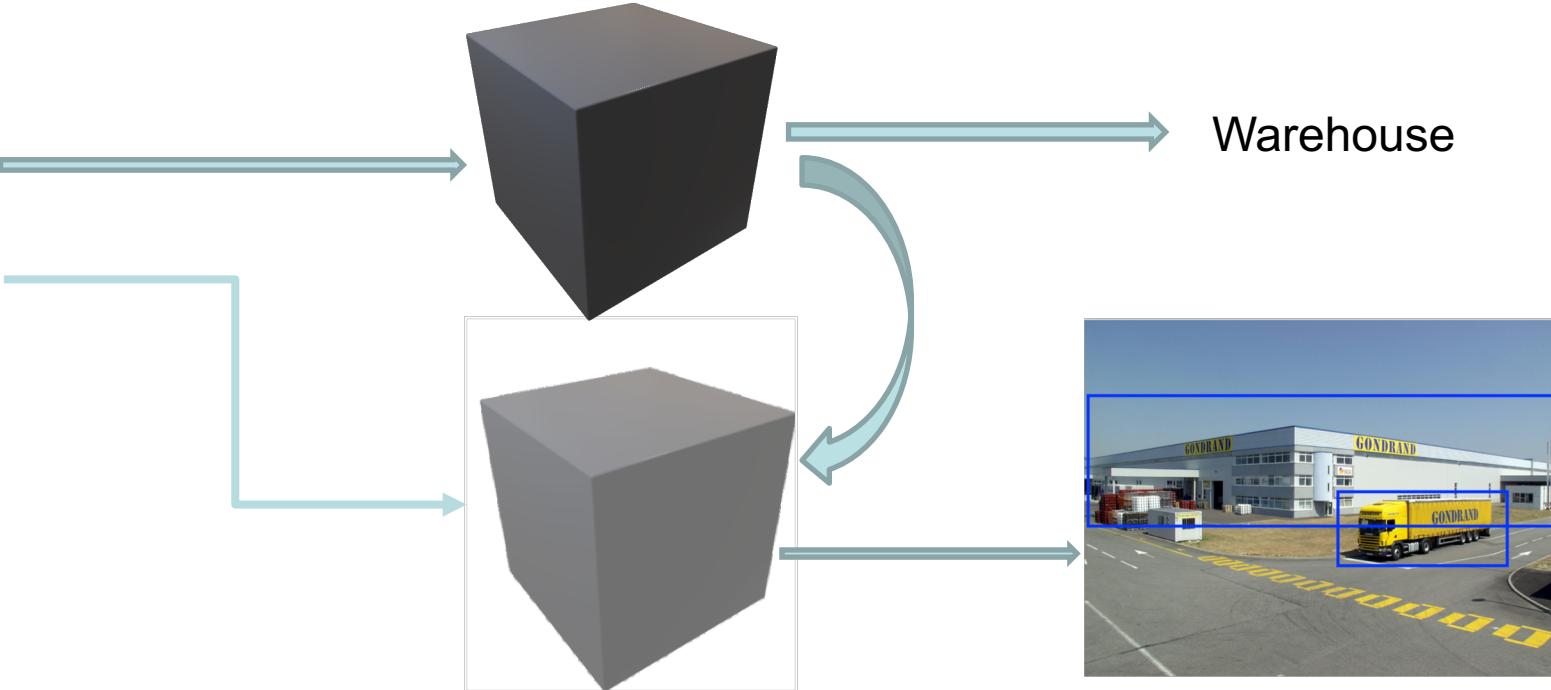
AI Model



Warehouse



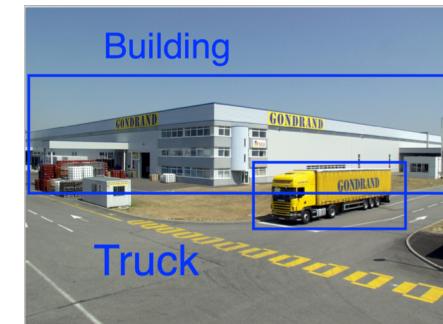
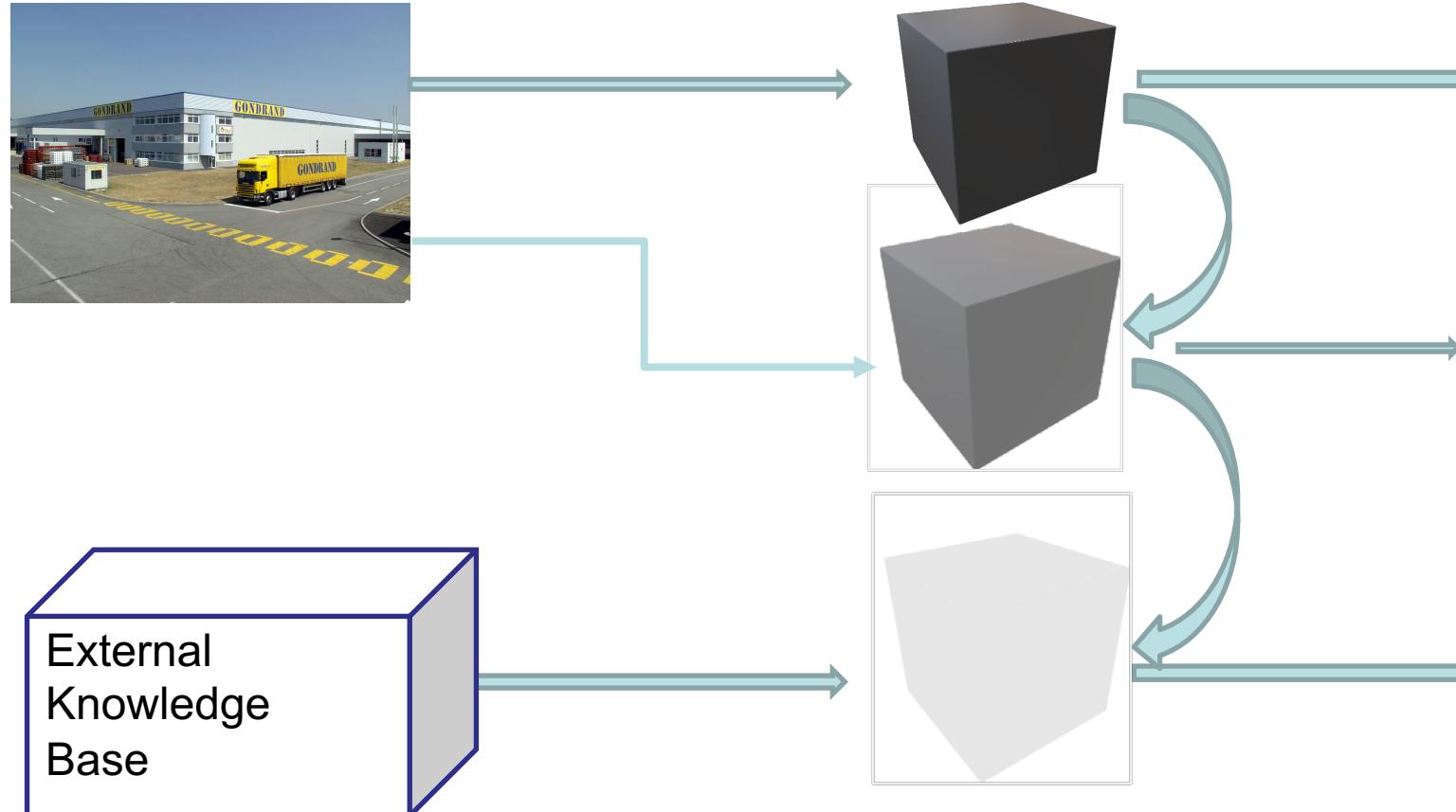
AI Model with some explanation



AI Model with some explanation

AI Model using semantics

Enhanced explanation using semantic web technology



Warehouse

This image contains building, truck, door, window which are usually found in warehouse. So it seems this picture is a Warehouse picture.¹



¹Derek, 2018

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- Questions?
- Other ideas how explanation can be enhanced?
- Next steps to go from here?

Thank you



Thank you!