Aalto University
School of Science
and Technology

Multilabel classification through structured output learning

Hongyu Su

Department of Computer Science
School of Science, Aalto University
hongyu.su@aalto.fi

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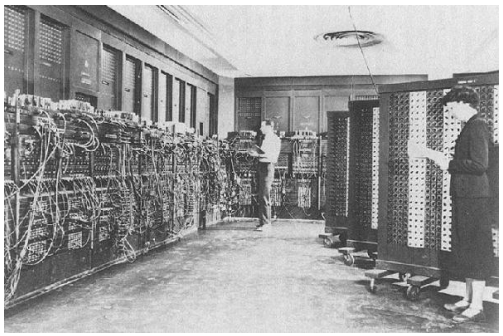
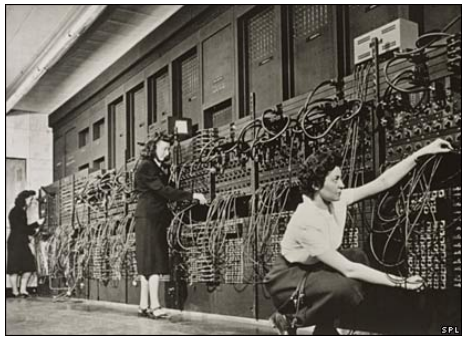
Machine learning

- In 1946, the first fully electronic computer was built, known as ENIAC.





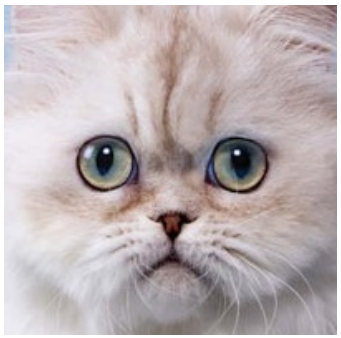
- In 1957, the perceptron algorithm was invented (Rosenblatt, 1958).
- In 1958, New York Times wrote perceptron as “the embryo of an electronic computer that [the Navy] expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence”.
- In 1959, Arthur Samuel defined machine learning as a “Field of study that gives computers the ability to learn without being explicitly programmed”.

Main scope of this dissertation

- The dissertation focuses on classification learning, and multilabel classification in particular.

Example: dog vs. cat?

- We have 5000 pictures of dog and 5000 pictures of cat.

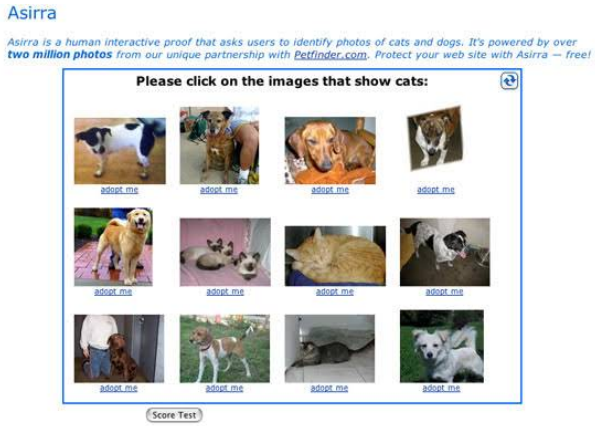



- Computer digitalize each picture into 100×100 pixels.
- Given a new picture, we want to answer: is it a dog or a cat?
- Simple task for human, dog, or cat.
- Golle (2008) claimed this is a difficult task for machines with only 82.7% *accuracy* (probability of getting a right answer).
- In 2013, 98.5% accuracy was reported in a Kaggle competition (https://www.kaggle.com/c/dogs-vs-cats).
- Why is this useful?

In human verification system

- Human verification system is a program that protects website from robots by generating and grading test that human can pass but machine cannot.
- CAPTCHA system (Ahn et al., 2003) uses distorted text.

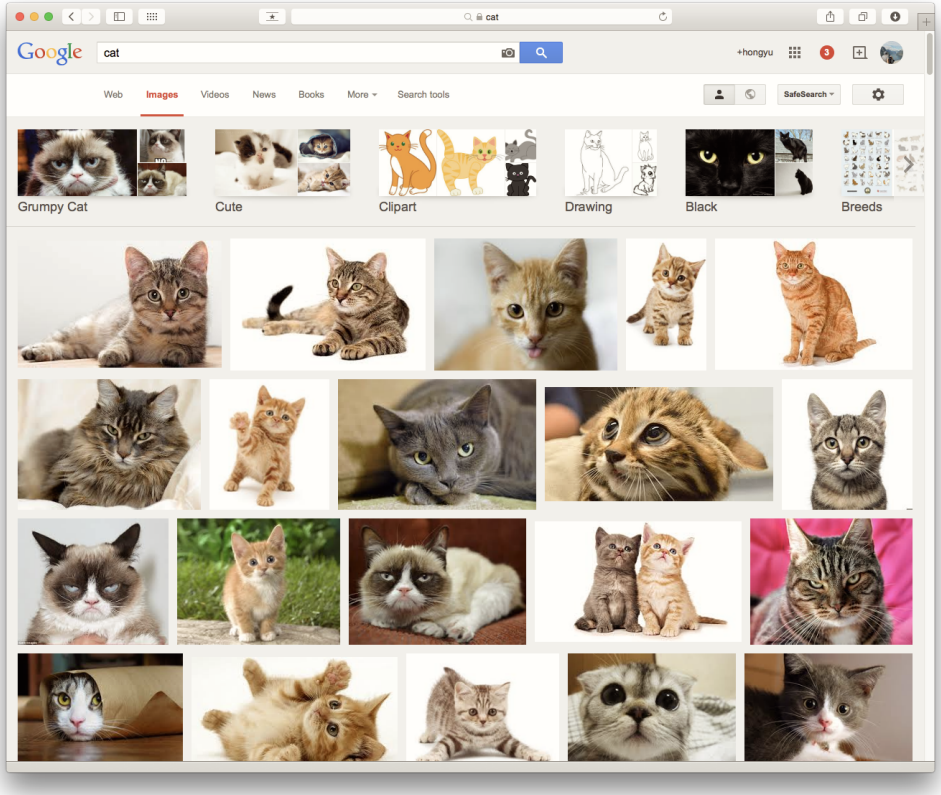
- ASIRRA system (Elson et al., 2007) uses images.



- To test if the ASIRRA system is safe from machine learning attack.
  - One should get all 12 pictures right!
  - Accuracy for machine is $(98.5\%)^{12} \approx 83.4\%$.

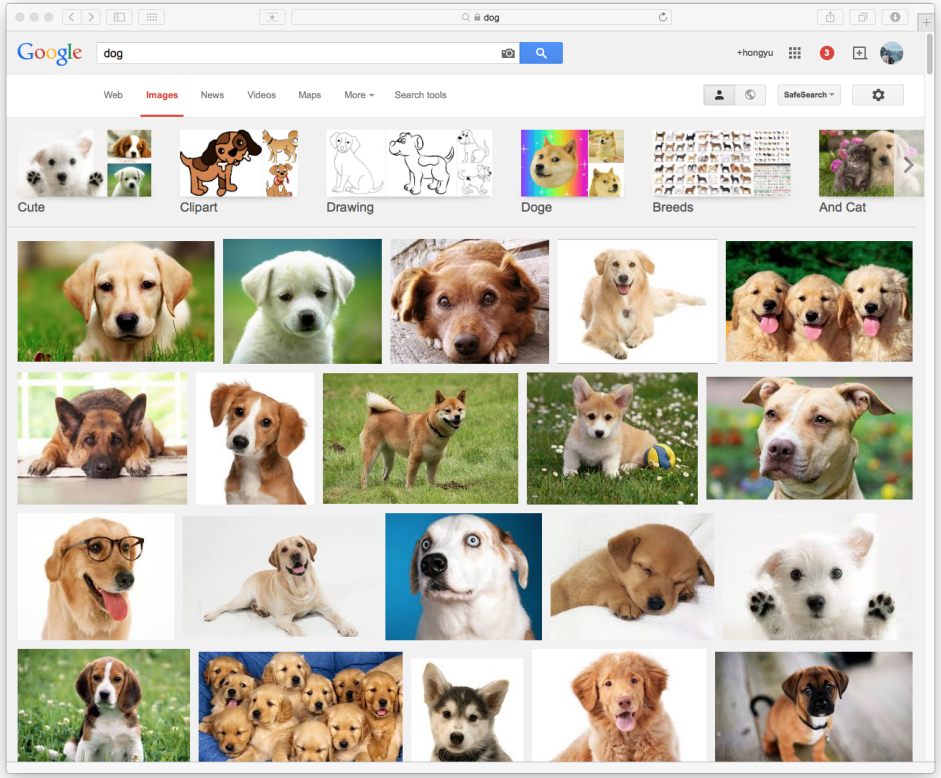
In search engine

- If machine can assign cat/dog to all pictures correctly, we can search pictures with keywords.
- Search all **cat** pictures.



In search engine

- If machine can assign cat/dog to all pictures correctly, we can search pictures with keywords.
- Search all **dog** pictures.



Single label classification

- In machine learning, the problem is known as *single label classification*.
  - Input is an object $\mathbf{x}$ (e.g., a picture).
  - Output is an attribute y called *label* (e.g., $y = +1$:dog, $y = -1$:cat).
  - Explore a set of known object and label pairs called *training data*

$$\{\underbrace{(\mathbf{x}_1, +1), \cdots, (\mathbf{x}_{5000}, +1)}_{\text{dog pictures}}, \underbrace{(\mathbf{x}_{5001}, -1), \cdots, (\mathbf{x}_{10000}, -1)}_{\text{cat pictures}}\}.$$

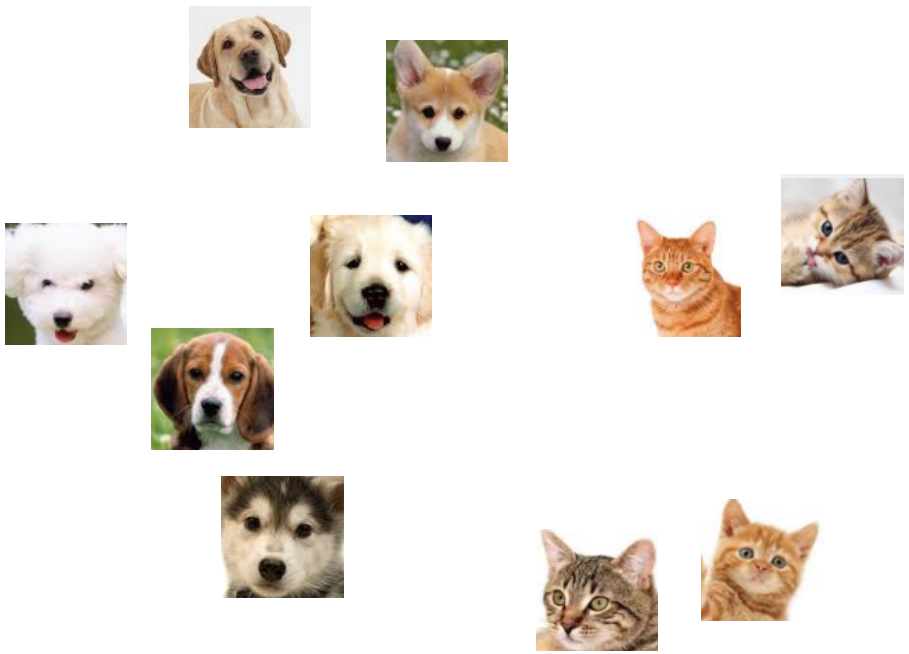
  - Learn a *mapping function f* that predicts the label of a new object.

$$\mathbf{x} \xrightarrow{f} y, y \in \{+1, -1\}.$$

- Many algorithms are available to tackle single label classification problems, e.g., support vector machines (Cortes and Vapnik, 1995), logistic regression (Chen and Rosenfeld, 1999).

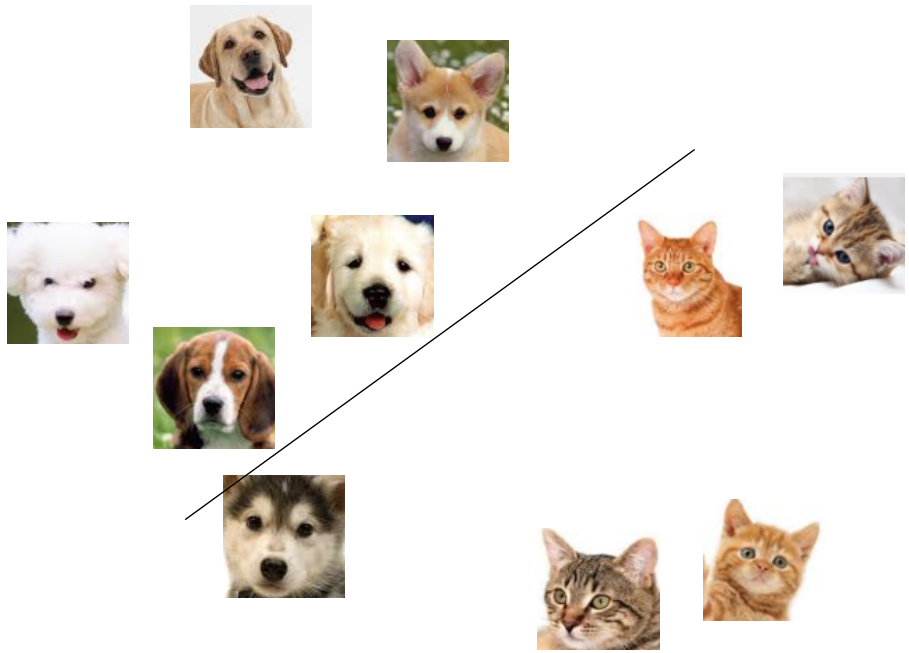
Support vector machine

- Represent objects into a feature space (e.g., points in 2D space.)
- A feature space is a high dimensional space made by *kernel functions* (Shawe-Taylor and Cristianini, 2004).



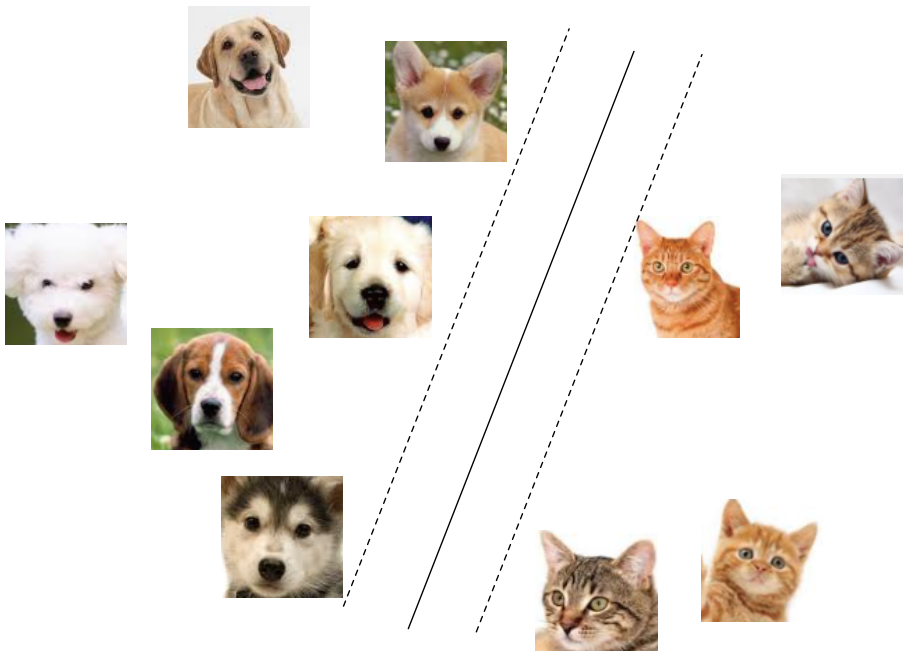
Support vector machine

- Find a *hyperplane* (*classifier*) to separate objects of two classes.
- Minimize the number of mistakes made by the classifier. This is known as *empirical risk minimization* (Vapnik, 1992).



Support vector machine

- We want the hyperplane to separate two classes with a big “gap”.
- “Gap” is known as *margin* which gives us enough confident to deal with new objects (Evgeniou et al., 1999, 2002).



Support vector machine

- Represent the new object into the same feature space.
- The classifier will generate the label of the new object according to its side.

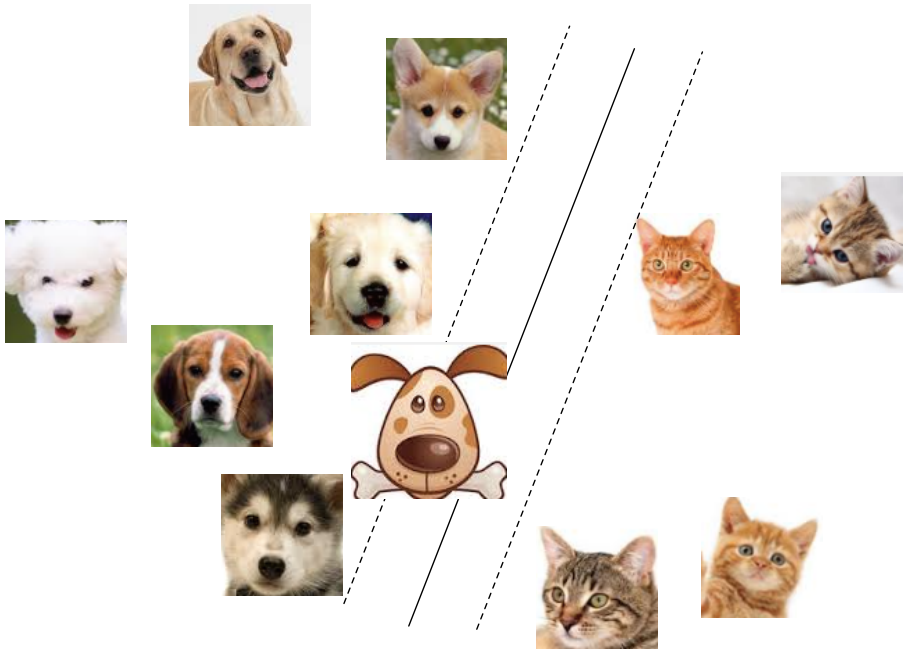


Image annotation task

- We are often interested in multiple attributes of a single picture.
- For example, we want to assign multiple tags to one picture.

$$\{\text{boat, sea, sun, beach, people, dog, cat}\}$$

- Correct annotations will allow us to search with multiple attributes.
- Search with **dog & cat**.

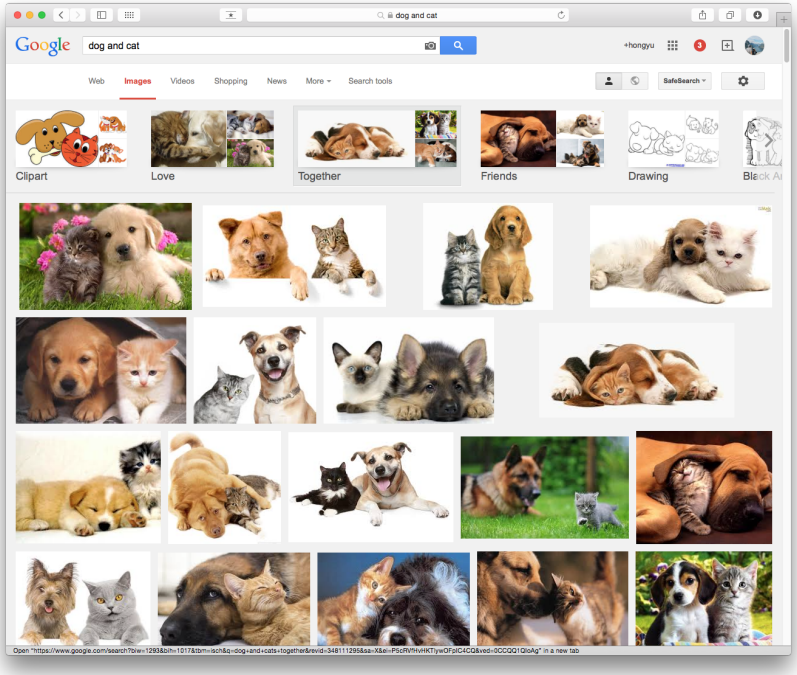


Image annotation task

- We are often interested in multiple attributes of a single picture.
- For example, we want to assign multiple tags to one picture.

$$\{\text{boat, sea, sun, beach, people, dog, cat}\}$$

- Correct annotations will allow us to search with multiple attributes.
- Search with **sun & beach & people**.

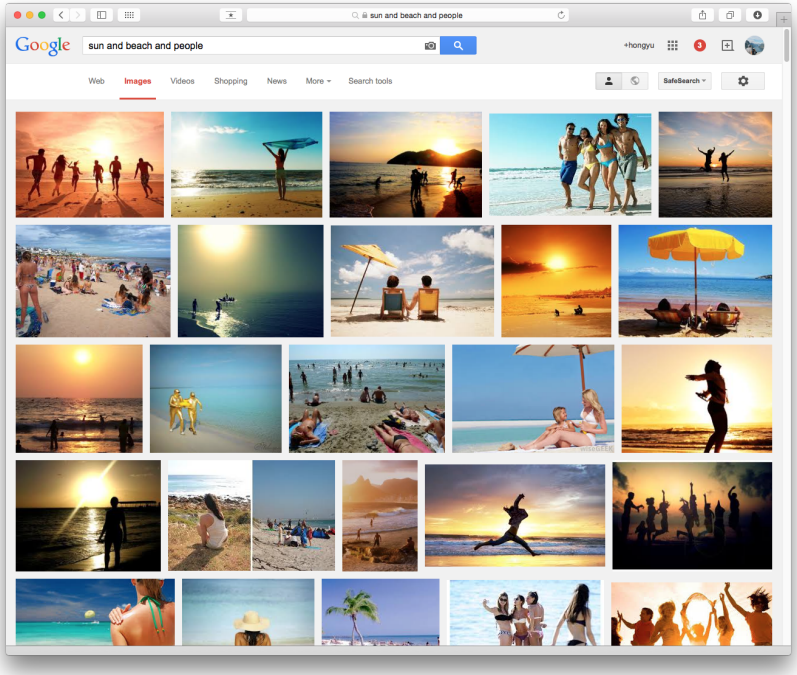
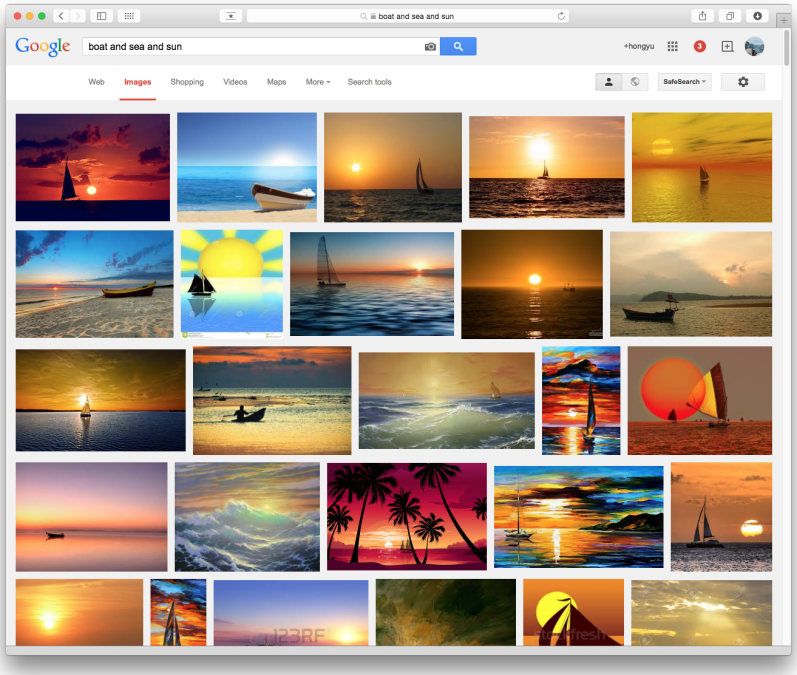


Image annotation task

- We are often interested in multiple attributes of a single picture.
- For example, we want to assign multiple tags to one picture.

$$\{\text{boat, sea, sun, beach, people, dog, cat}\}$$

- Correct annotations will allow us to search with multiple attributes.
- Search with **boat & sea & sun**.



Multilabel classification

- The problem is known as *multilabel classification*, which is a natural extension to single label classification.
  - Input **x** is an object (e.g., a picture).
  - Output **y** are multiple attributes called *multilabel*

$$\mathbf{y} = (\underbrace{+1}_{\text{boat}}, \underbrace{+1}_{\text{sea}}, \underbrace{-1}_{\text{sun}}, \underbrace{-1}_{\text{beach}}, \underbrace{+1}_{\text{people}}, \underbrace{-1}_{\text{dog}}, \underbrace{-1}_{\text{cat}}).$$

  - Explore a set of known object and label pairs called training data.
  - Learn a *mapping function* that predicts the best multilabel of a new object.

$$\mathbf{x} \xrightarrow{f} \mathbf{y} = (y_1, \cdots, y_k).$$

- Multilabel classification is an active research field in machine learning.

Applications

- Pictures can associate with multiple tags.

$$(\underbrace{+1}_{\text{boat}}, \underbrace{+1}_{\text{sea}}, \underbrace{-1}_{\text{sun}}, \underbrace{-1}_{\text{beach}}, \underbrace{-1}_{\text{people}}, \underbrace{+1}_{\text{ice}}, \underbrace{+1}_{\text{land}})$$

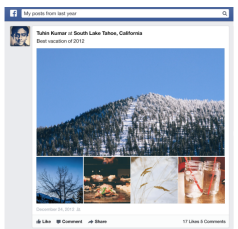
- News articles can be assigned to multiple categories.

$$(\underbrace{+1}_{\text{news}}, \underbrace{+1}_{\text{economics}}, \underbrace{-1}_{\text{sports}}, \underbrace{-1}_{\text{politics}}, \underbrace{-1}_{\text{movie}}, \underbrace{-1}_{\text{science}}, \underbrace{-1}_{\text{art}})$$

- Drugs can be effective for multiple symptoms.

$$(\underbrace{+1}_{\text{heart}}, \underbrace{+1}_{\text{stroke}}, \underbrace{+1}_{\text{blood}}, \underbrace{+1}_{\text{fever}}, \underbrace{-1}_{\text{digest}}, \underbrace{-1}_{\text{liver}}, \underbrace{+1}_{\text{swelling}})$$

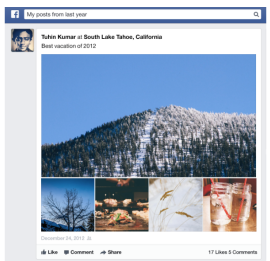
- Information can spread through multiple users in social network.



$$(\underbrace{+1}_{\text{Ted}}, \underbrace{-1}_{\text{Alice}}, \underbrace{+1}_{\text{David}}, \underbrace{-1}_{\text{Mark}}, \underbrace{+1}_{\text{Alex}}, \underbrace{-1}_{\text{Zoe}}, \underbrace{-1}_{\text{Frank}})$$

How to solve multilabel classification?

- Reduce the multilabel classification problem as a collection of single label classification problems.
- Solve each individual problem independently.
- Concatenate the predictions.



$\xrightarrow{f}$

$$(\underbrace{?}_{\text{Ted}}, \underbrace{?}_{\text{Alice}}, \underbrace{?}_{\text{David}}, \underbrace{?}_{\text{Mark}}, \underbrace{?}_{\text{Alex}}, \underbrace{?}_{\text{Zoe}}, \underbrace{?}_{\text{Frank}})$$

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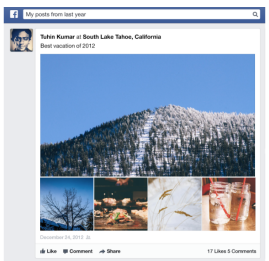

$\xrightarrow{f_1}$ $(\underbrace{+1}_{\text{Ted}}, \underbrace{\ }_{\text{Alice}}, \underbrace{\ }_{\text{David}}, \underbrace{\ }_{\text{Mark}}, \underbrace{\ }_{\text{Alex}}, \underbrace{\ }_{\text{Zoe}}, \underbrace{\ }_{\text{Frank}})$

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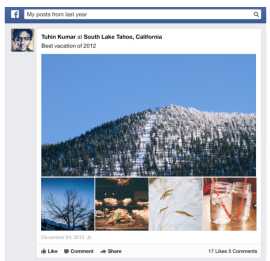

$\xrightarrow{f_2}$

$(\underbrace{\ }_{\text{Ted}}, \underbrace{-1}_{\text{Alice}}, \underbrace{\ }_{\text{David}}, \underbrace{\ }_{\text{Mark}}, \underbrace{\ }_{\text{Alex}}, \underbrace{\ }_{\text{Zoe}}, \underbrace{\ }_{\text{Frank}})$

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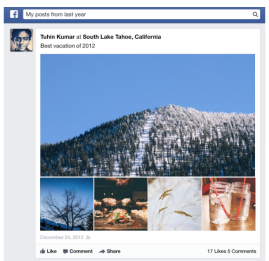

$\xrightarrow{f_3}$

$$(\underbrace{\ }_{\text{Ted}}, \underbrace{\ }_{\text{Alice}}, \underbrace{+1}_{\text{David}}, \underbrace{\ }_{\text{Mark}}, \underbrace{\ }_{\text{Alex}}, \underbrace{\ }_{\text{Zoe}}, \underbrace{\ }_{\text{Frank}})$$

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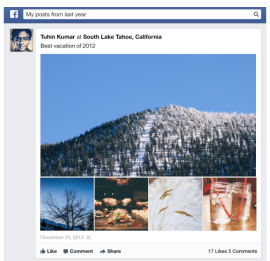

$\xrightarrow{f_4}$

$$(\underbrace{\ }_{\text{Ted}}, \underbrace{\ }_{\text{Alice}}, \underbrace{\ }_{\text{David}}, \underbrace{-1}_{\text{Mark}}, \underbrace{\ }_{\text{Alex}}, \underbrace{\ }_{\text{Zoe}}, \underbrace{\ }_{\text{Frank}})$$

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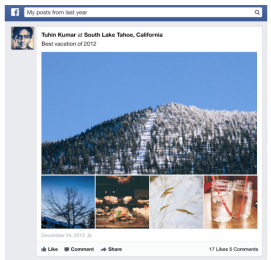
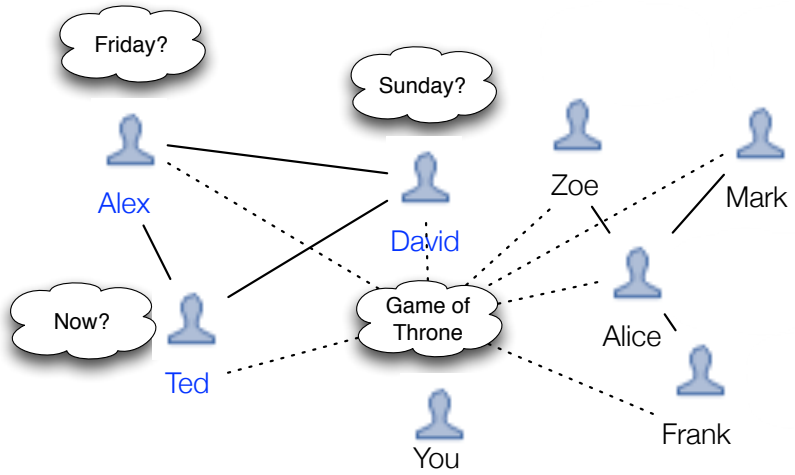


$$\overset{f_1,\cdots,f_7}{\rightarrow} (\underbrace{+1}_{\text{Ted}}, \underbrace{-1}_{\text{Alice}}, \underbrace{+1}_{\text{David}}, \underbrace{-1}_{\text{Mark}}, \underbrace{+1}_{\text{Alex}}, \underbrace{-1}_{\text{Zoe}}, \underbrace{-1}_{\text{Frank}})$$

Label correlations

- Multiple attributes are often closely related. Similar attributes will have similar responses to an input.
- Social network analysis: friends have similar hobbies.

$$(\underbrace{+1}_{\text{Ted}}, \underbrace{-1}_{\text{Alice}}, \underbrace{+1}_{\text{David}}, \underbrace{-1}_{\text{Mark}}, \underbrace{+1}_{\text{Alex}}, \underbrace{-1}_{\text{Zoe}}, \underbrace{-1}_{\text{Frank}})$$



- Document classification: A news about politics may be also about economics.
- Label correlations can help make better predictions.

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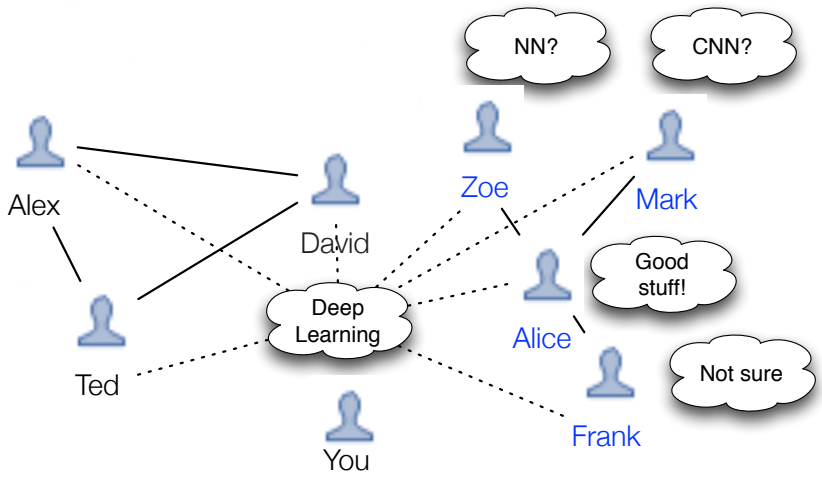

- Document classification: A news about politics may be also about economics.
- Label correlations can help make better predictions.

Structured output prediction

- We want to explore the correlations of attributes to improve the performance on multilabel classification problems.
- In statistics, graph is a natural way to model correlations. *Output graph* is defined by
  - Nodes correspond to multiple attributes.
  - Edges correspond to correlations of attributes.
- *Structured output prediction* method
  - predicts multiple attributes of an object at the same time.
  - explores the correlations described by an output graph.

Contributions of this dissertation

- The main contributions are several structured output learning algorithms that improve the performance on multilabel classification problems.
- In addition, it also contributes to theoretical studies on the performance of the proposed learning algorithms.
- For the multilabel classification problems where the output graph is given *apriori*.
  - Improve the performance on drug sensitivity prediction problems (Su et al., 2010).
  - Predict reliably the spread of a content in social networks (Su et al., 2014).
- For general multilabel classification problems without predefined output graph
  - Several ensemble methods that combine a collection of structured output learners (Su and Rousu, 2011, 2013, 2014).
  - A joint learning and inference framework with theoretical guarantee on the performance (Marchand et al., 2014).

Future work

- Proposed algorithms can be applied to many real world multilabel classification tasks.
  - Image annotation, document classification, drug activity prediction, social network analysis.
  - Sentiment analysis, music categorization, protein function prediction, etc.
- Algorithm developments:
  - Select and combine a collection of random output graphs to discover latent structure.
  - Develop new and fast inference algorithm that allows learning on large scale datasets.

Image source

- Eniac pictures are from Wikipedia.
- Animal pictures are from Google.
- CAPTCHA system picture is from http://www.captcha.net.
- ASIRRA system picture is from http://research.microsoft.com/en-us/um/redmond/projects/asirra/.
- Application pictures are from Google.
- Social network pictures are from Facebook.

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Thank you!