CS260: Machine Learning Theory
Lecture 1: Course Introduction

Jenn Wortman Vaughan

September 26, 2011

What is machine learning?

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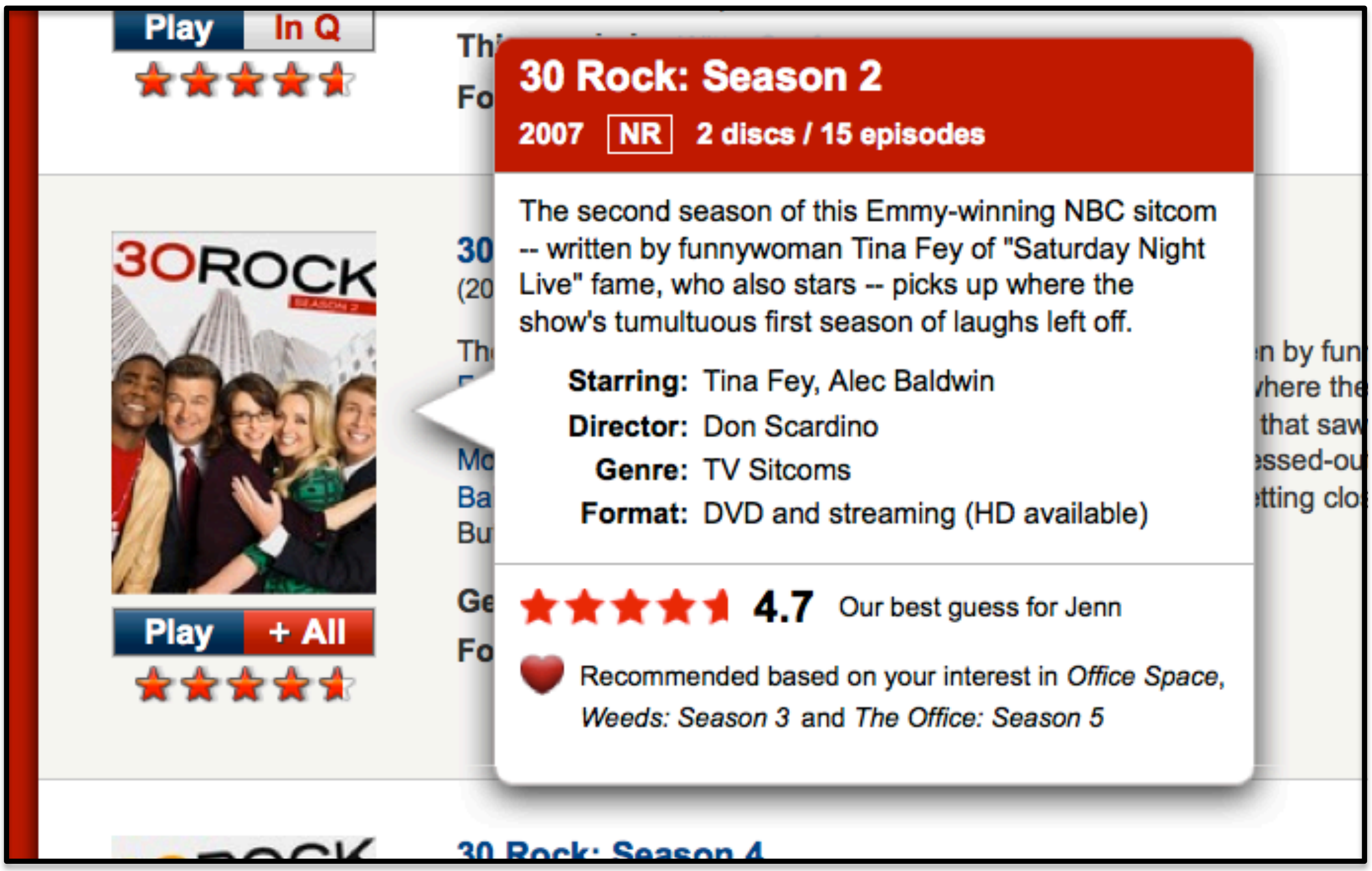
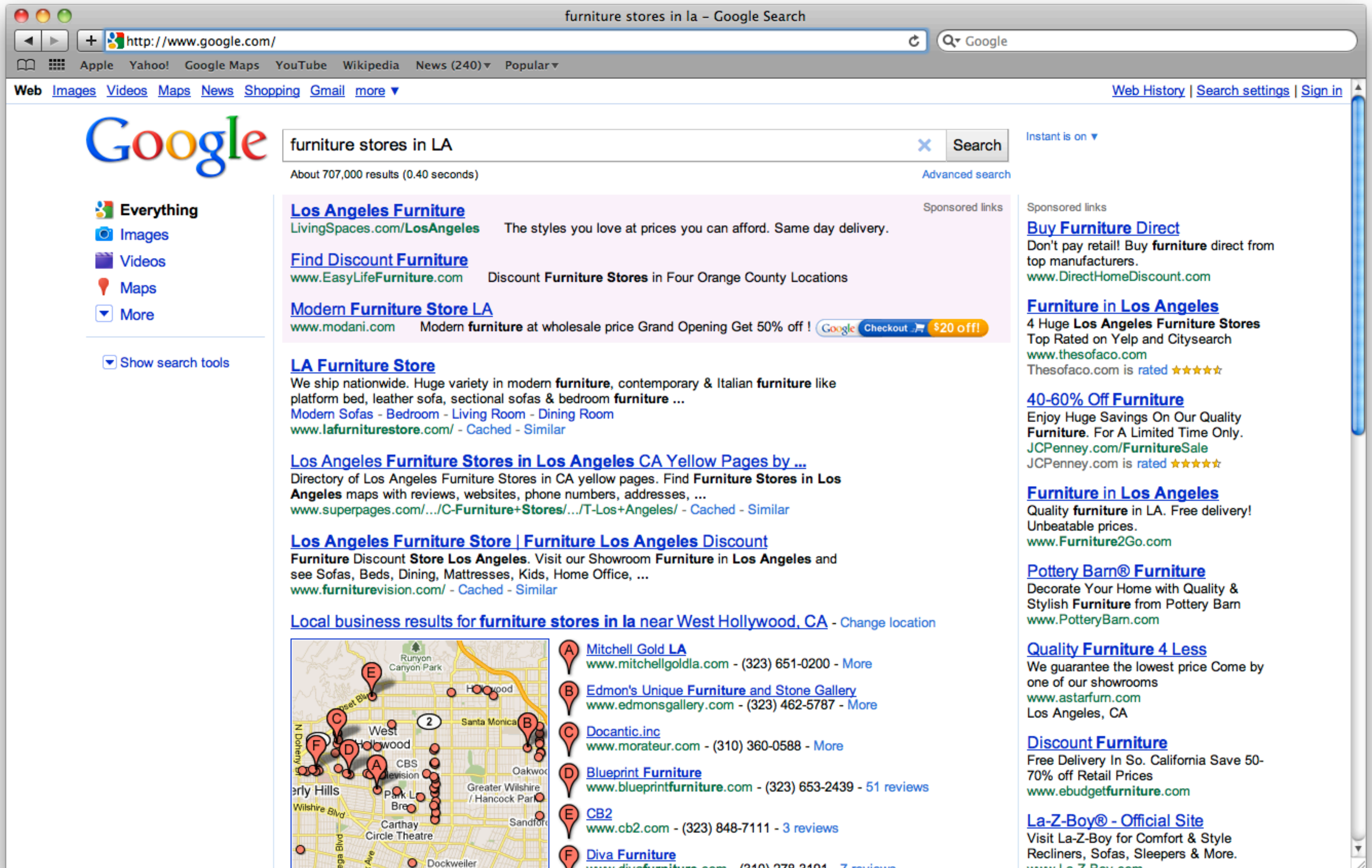
Machine learning is the study of how to use past observations or experience to automatically and efficiently learn to make better predictions or choose better actions in the future

Movie Recommendations

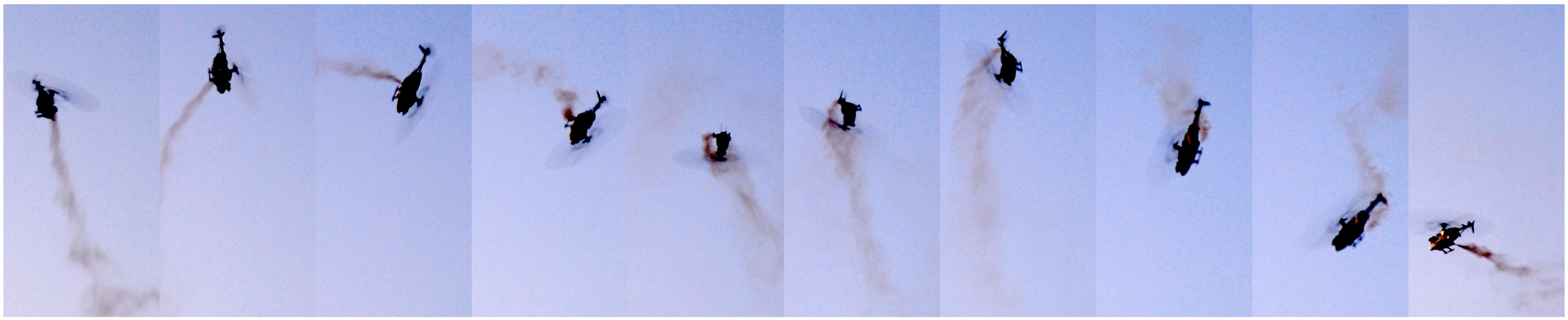


Click Prediction



Autonomous Flight

Helicopter rolls:



Helicopter flips:

Other Examples

- Medical diagnosis
- Handwritten character recognition
- Customer segmentation (marketing)
- Document segmentation (classifying news)
- Spam filtering
- Weather prediction and climate tracking
- Gene prediction
- Face recognition

Spam Prediction

We are given a set of labeled email messages

To: Jenn Wortman Vaughan
From: Jeff Vaughan
Subject: Plans for tonight ✔

To: Jenn Wortman Vaughan
From: Bob Smith
Subject: V14GR4 4 U ✖

To: Jenn Wortman Vaughan
From: Jens Palsberg
Subject: Meeting ✔

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Goal is to predict labels of new messages that arrive

To: Jenn Wortman Vaughan
From: NIPS Committee
Subject: Paper decision ?

A Classification Problem

First we need a way to represent the data…

“Jenn”	“260”	“Viagra”	Known Sender	Spelling Bad	Spam?
1	1	0	0	1	0
1	0	0	1	0	0
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"feature vector"

"label"

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- Disjunctions (spam if not known or not "260")
- Thresholds (spam if "Jenn"+"260"+known < 2)

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"concept class" or "function class" or "hypothesis class"

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"prediction rule" or "hypothesis" or "concept"

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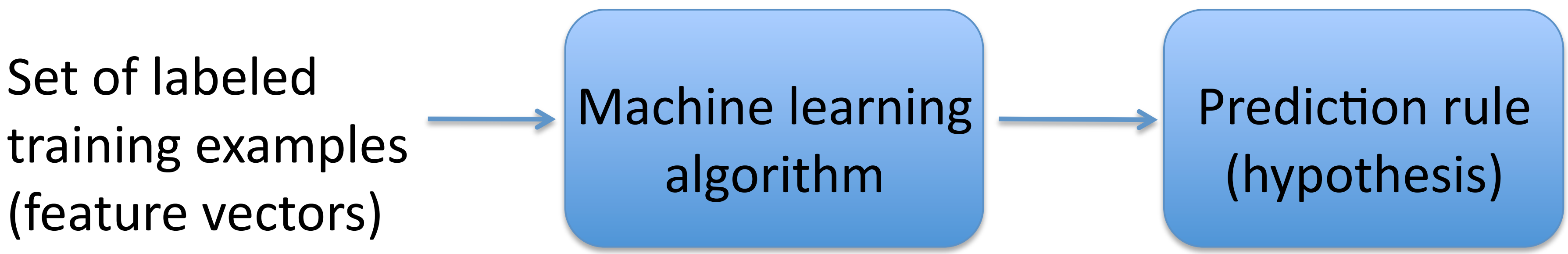
Finally, we need an algorithm…

Typical Classification Problem



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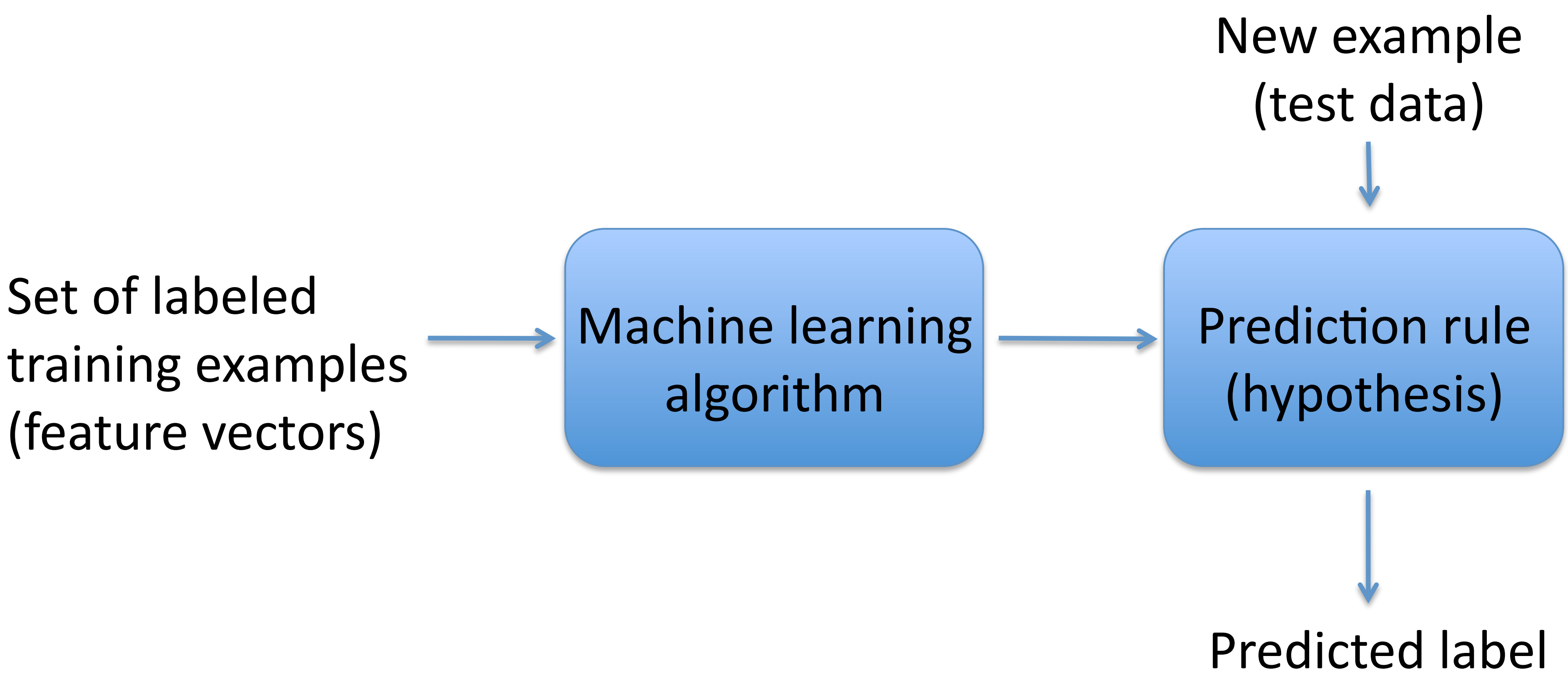

Batch Versus Online Learning

What if there are no clear training and test sets?

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The goal is now to update the prediction rule over time while making as few mistakes as possible

Other Learning Settings

- Unsupervised learning (clustering)
- Semi-supervised learning
- Active learning
- Reinforcement learning

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… why particular algorithms may or may not perform well under various conditions

This generates intuition useful for algorithm design

Questions We Ask

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- What are the intrinsic properties of a learning problem that impact the amount of data we need?
- How much prior information or domain knowledge do we need to learn effectively?
- Are simpler hypotheses always better? Why?
- How should we trade off the standard notions of efficiency (time, space) with data efficiency?

Course Overview

1. Classification and the "probably approximately correct" (PAC) model of learning

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3. Some of learning theory's success stories, including boosting and support vector machines
4. Recent research topics (time permitting)

Things We Will NOT Cover

- Implementation tricks
- Feature design
- Particular application domains (natural language, vision, robotics, search, etc.)
- Commercial uses of machine learning

… but you are welcome to explore some of these topics as one part of your final project

Who should take this class?

- Students with a background in machine learning who want to know more about the theoretical foundations
- Students with a background in CS theory who want to know more about learning

- Prerequisites: comfort with probability theory, comfort reading & writing mathematical proofs

Course Logistics

Reading Material

There is no required textbook for this class

Lecture notes and links to supplementary reading material will be posted regularly at:

`http://www.cs.ucla.edu/~jenn/courses/F11.html`

Check this website often!!

Breakdown of Grades

Four homework assignments (60%)

- Mostly analysis and proofs
- No coding required

Final Project (40%)

- In-class presentation and written report

Academic Honesty Policy

Collaboration is strongly encouraged, but…

- Each student must write down his or her own solutions independently in his or her own words.
- Each student must submit a list of anyone with whom the assignment was discussed.
- All sources (internet included) must be credited.
- Solution sets from this course or any other course may not be used under any circumstances.

PTEs

If you would like a PTE for this class, please

- Come to class today and Wednesday
- Send me an email after Wednesday's class telling me a little about your background

Logistical Loose Ends

- This course counts toward AI majors/minors
- Auditors are welcome as long as there is space – please reserve seats for students who are enrolled
- All of this info and more is on the course website

Models of Learning

Models of Learning

- A learning model must specify several things
  - What are we trying to learn?
  - What kind of data is available?
  - How is the data presented to the learner?
  - What type of feedback does the learner receive?
  - What is the goal of the learning process?

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  - What are we trying to learn?
  - What kind of data is available?
  - How is the data presented to the learner?
  - What type of feedback does the learner receive?
  - What is the goal of the learning process?
- To provide valuable insight, a learning model must be robust to minor variations in its definition

The Consistency Model

- **Definition:** We say that algorithm A learns concept class C in the consistency model if given a set of labeled examples S, A produces a concept $c \in C$ consistent with S if one exists and states that none exists otherwise.

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- **Definition:** We say that a class C is efficiently learnable in the consistency model if there exists an efficient algorithm A that learns C.

Example: Monotone Conjunctions

Guitar	Fast beat	Male singer	Acoustic	New	Liked
1	0	0	1	1	1
1	1	1	0	0	0
0	1	1	0	1	0
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- Find all of the variables that are true in every positive example.
- Let *c* be the conjunction of these variables.
- Output *c* if it is consistent with all negative examples; otherwise, output none.

Example: DNFs

Guitar	Fast beat	Male singer	Acoustic	New	Liked
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DNF = the set of all disjunctions of conjunctions

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Trivial to learn in the consistency model!

What is wrong with this model?