Machine Learning
V07: ML System Design

System development: What to give priority?
Example: Learning to read checks end-to-end

With material from Andrew Y. Ng, Coursera
See also [LeCun et al, “Gradient-Based Learning…”, 1998]

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Educational objectives

- **Remember error-** and **ceiling analysis** as well as the initial **24h hack** as tools to be successful in ML
- **Know how** to **design** and **prioritize** complete machine learning **system pipelines**
- **Appreciate** the **elegance** of the design **that enables ent-to-end learning** for the check reading application of LeCun et al.

1. SYSTEM DEVELOPMENT: WHAT TO GIVE PRIORITY?

Example 1: Building a spam classifier

```
From: cheapsales@buystufffromme.com
To: stdm@zhaw.ch
Subject:  Buy now!

Deal of the week! Buy now!
Rolex w4tchs - $100
Med1cine (any kind) - $50
Also low cost M0rgages
available.
```

```
From: Renate Stadelmann
To: stdm@zhaw.ch
Subject:  Holiday plans

Hi Thilo,
was talking to Philipp about
plans for New Year. Sauna and
surfing in winter? ;-)
Love, Renate
```

$$x = \begin{array}{cl} \begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \\ \vdots \\ 1 \\ \vdots \end{bmatrix} & \begin{matrix} \#Thilo \\ \#buy \\ \#deal \\ \#discount \\ \vdots \\ \#now \\ \vdots \end{matrix} \end{array}, \quad x_j = \begin{cases} 1: word\ occurrs\ in\ mail \\ 0: otherwise \end{cases}$$

Supervised learning task

- x: features of email ➔ y: 1 (spam) or 0 (non-spam)

Practical features

- Create **list of** 50’000 **most frequent words** in training set

Example 1: Building a spam classifier (contd.)
How to prioritize *algorithmic* work?

How to best invest the time to make it work (i.e., have low error)?
- **Collect** lots of **data** (e.g., "honeypot" project)?
- **Develop** sophisticated **features**?
  - …based on email routing information from email **header**
  - …for message **body**
    ➔ Treat "discount" and "discounts" as same word? "Deal" and "Dealer"?
    ➔ Features about punctuation?
- **Develop** sophisticated **algorithm** to detect misspellings?
  ➔ e.g. "m0rtgage", "med1cine", "w4tches"

Advice
- Take **24h** to implement (rather: **hack**) a **complete system** including scoring
- Use diagnostics to decide where to improve

Recommendation
1. Start with a **simple algorithm** that can be **implement**ed **quickly**
   ➔ Implement it and test it on cross-validation data
2. Plot **learning curves** to diagnose if more data, more features, etc. are likely to help
3. **Error analysis**: Manually examine the CV examples that where misclassified
   ➔ Is there a **systematic trend** in what type of examples are **misclassified**?

Example 1: Building a spam classifier (contd.)

Error analysis

Assume the following experimental outcome
- $N_{CV} = 500$ emails in CV set
- 100 emails are misclassified

➔ **Manually examine** the 100 **errors**

Categorization based on
1. **Type** of email
2. **Cues** (feature candidates) that would have helped the algorithms to classify correctly

Type	Number
Pharma	12
Replica / faked goods	4
Phishing	53
Other	31

Cues	Number
Deliberate misspellings ("m0rgage", "med1cine", etc.)	5
Unusual email routing	16
Unusual punctuation ("!!!!!!!" etc.)	32

quite rare

this might help

Example 1: Building a spam classifier (contd.)
The importance of numerical evaluation (error analysis 2)

Should a stemmer **be used** (e.g., free “Porter stemmer”)?
- Treats “discount” / ”discounts” / “discounted” / “discounting” as the same word
- Makes e.g. “universe” / “university” undistinguishable

➔ Error analysis doesn’t help much in deciding

Solution
- **Try** with & without
- **Compare numerical results** ➔ need a **single performance metric** for that (e.g. CV error; F-score)

Method	CV error
Original: without stemming	5%
With stemming	3%
Additional: distinguishing upper vs. lower case	3.2%

good idea!

doesn’t help

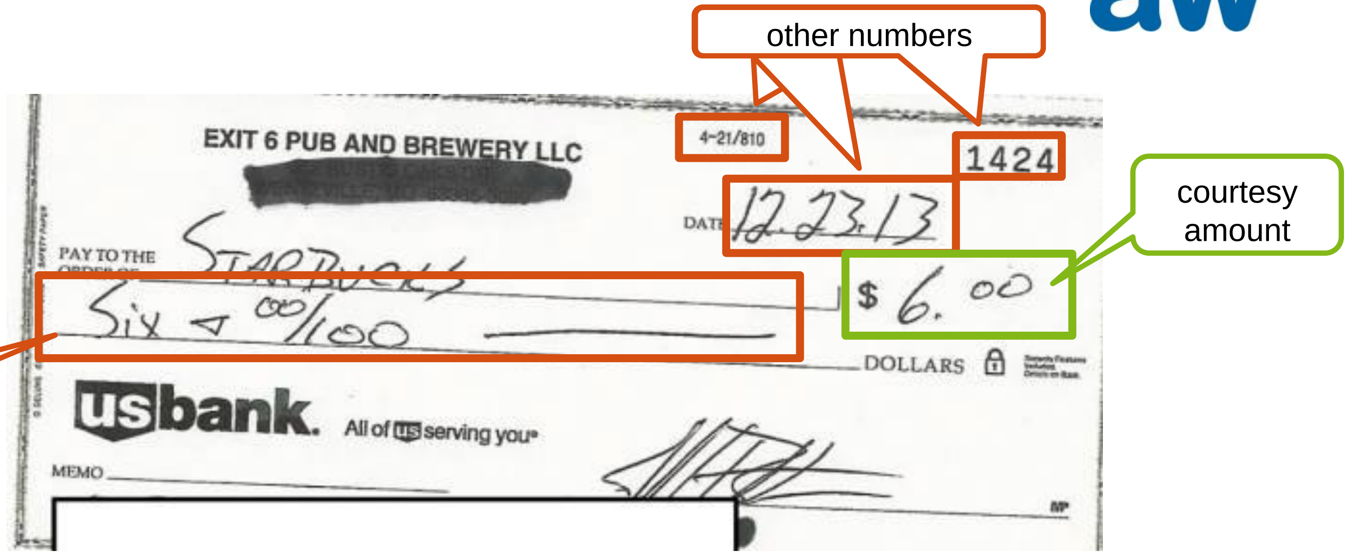
- Attention: If classes are **skewed** (e.g., cancer prediction), **regard** recall-precision **trade-off**
  ➔ Use for example the F-measure instead of pure error (→ compare V03)
  ➔ Give the **rare class** the **label 1/true**

Example 2: Check reading application

Problem description:

- Read amount of $6
- Easy for humans, but time-consuming

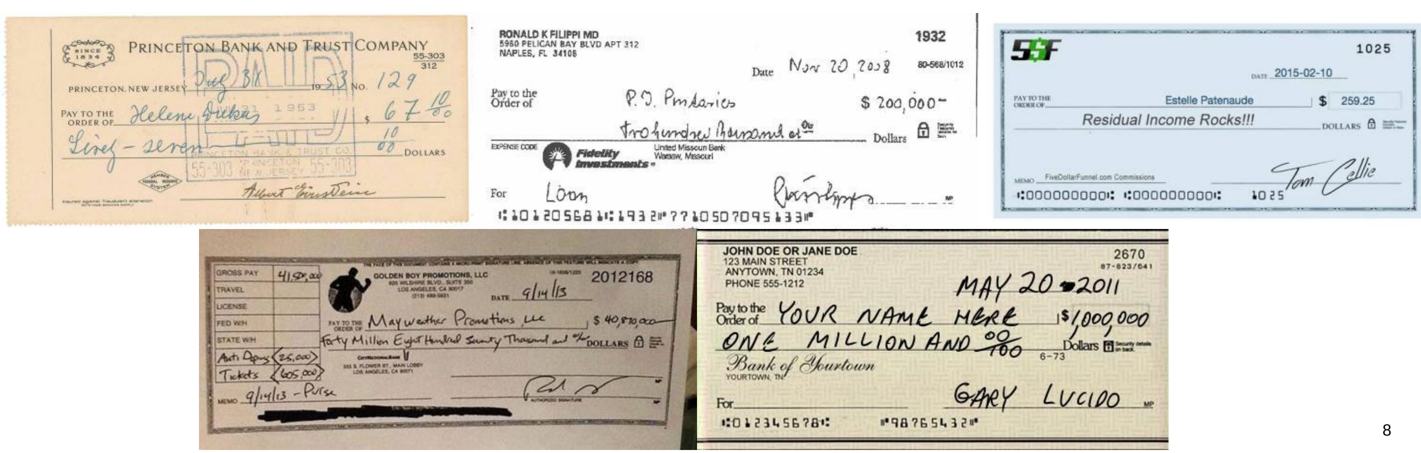
➔ Automation wanted



legal amount

Challenge:

- Which number?
- Diversity



Example 2: Check reading application (contd.)

What part of the *pipeline* to improve next?

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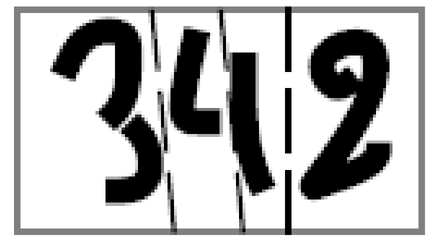
Challenge

- Identify correct character string (*«342»*) on a piece of paper
- Therefore:
  - **Detect** all handwritten strings
  - [**Identify** correct string (containing the amount)]
  - Find correct **segmentation**
  - **Recognize** individual characters



System pipeline

- **What part** of the pipeline should you **spend** the **most time** trying to improve**?**
- Note: Identification of the correct string is omitted here (could be placed at the end)

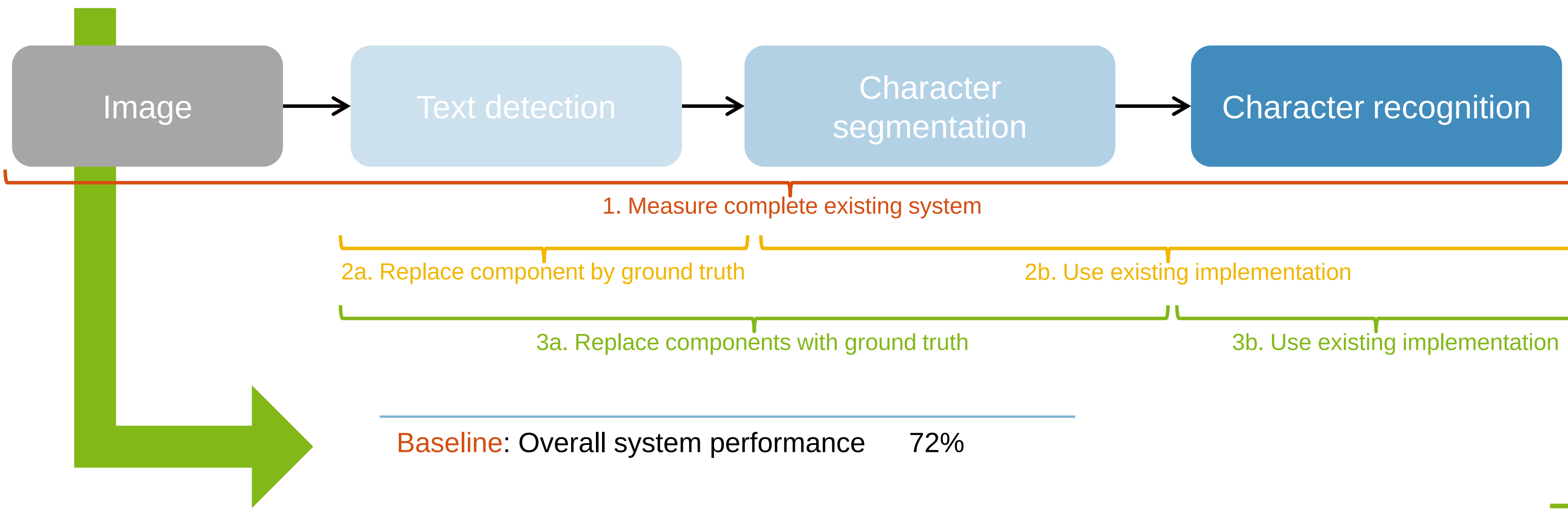
Image → Text detection → Character segmentation → Character recognition

Example 2: Check reading application (contd.)

Ceiling analysis: Attributing errors to individual components

Ceiling analysis

1. Baseline ➔ measure the (CV) performance of the complete pipeline
2. Replace first component with ground truth (perfect results) ➔ measure performance
3. Replace next component with ground truth ➔ measure performance
4. …



Baseline: Overall system performance	72%

2. SYSTEM EXAMPLE: LEARNING TO READ CHECKS END-TO-END

(Just the idea – details in appendix)

A landmark work in Machine *Learning*

LeCun et al., "Gradient-Based Learning Applied to Document Recognition", 1998

Gradient-Based Learning Applied to Document Recognition -> LeNet 5

Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner

Abstract—

Multilayer Neural Networks trained with the backpropagation algorithm constitute the best example of a successful Gradient-Based Learning technique. Given an appropriate network architecture, Gradient-Based Learning algorithms can be used to synthesize a complex decision surface that can classify high-dimensional patterns such as handwritten characters, with minimal preprocessing. This paper reviews various methods applied to handwritten character recognition and compares them on a standard handwritten digit recognition task. Convolutional Neural Networks, that are specifically designed to deal with the variability of 2D shapes, are shown to outperform all other techniques.

Real-life document recognition systems are composed of multiple modules including field extraction, segmentation, recognition, and language modeling. A new learning paradigm, called Graph Transformer Networks (GTN), allows such multi-module systems to be trained globally using Gradient-Based methods so as to minimize an overall performance measure.

Two systems for on-line handwriting recognition are described. Experiments demonstrate the advantage of global training, and the flexibility of Graph Transformer Networks.

A Graph Transformer Network for reading bank check is also described. It uses Convolutional Neural Network character recognizers combined with global training techniques to provides record accuracy on business and personal checks. It is deployed commercially and reads several million checks per day.

Keywords— **Neural Networks, OCR, Document Recognition, Machine Learning, Gradient-Based Learning, Convolutional Neural Networks, Graph Transformer Networks, Finite State Transducers.**

NOMENCLATURE

- GT Graph transformer.
- GTN Graph transformer network.
- HMM Hidden Markov model.
- HOS Heuristic oversegmentation.
- K-NN K-nearest neighbor.
- NN Neural network.
- OCR Optical character recognition.
- PCA Principal component analysis.
- RBF Radial basis function.
- RS-SVM Reduced-set support vector method.
- SDNN Space displacement neural network.
- SVM Support vector method.
- TDNN Time delay neural network.
- V-SVM Virtual support vector method.

The authors are with the Speech and Image Processing Services Research Laboratory, AT&T Labs-Research, 100 Schulz Drive Red Bank, NJ 07701. E-mail: {yann,leonb,yoshua,haffner}@research.att.com. Yoshua Bengio is also with the Département d'Informatique et de Recherche Opérationelle, Université de Montréal, C.P. 6128 Succ. Centre-Ville, 2920 Chemin de la Tour, Montréal, Québec, Canada H3C 3J7.

I. INTRODUCTION

Over the last several years, machine learning techniques, particularly when applied to neural networks, have played an increasingly important role in the design of pattern recognition systems. In fact, it could be argued that the availability of learning techniques has been a crucial factor in the recent success of pattern recognition applications such as continuous speech recognition and handwriting recognition.

The main message of this paper is that better pattern recognition systems can be built by relying more on automatic learning, and less on hand-designed heuristics. This is made possible by recent progress in machine learning and computer technology. Using character recognition as a case study, we show that hand-crafted feature extraction can be advantageously replaced by carefully designed learning machines that operate directly on pixel images. Using document understanding as a case study, we show that the traditional way of building recognition systems by manually integrating individually designed modules can be replaced by a unified and well-principled design paradigm, called *Graph Transformer Networks*, that allows training all the modules to optimize a global performance criterion.

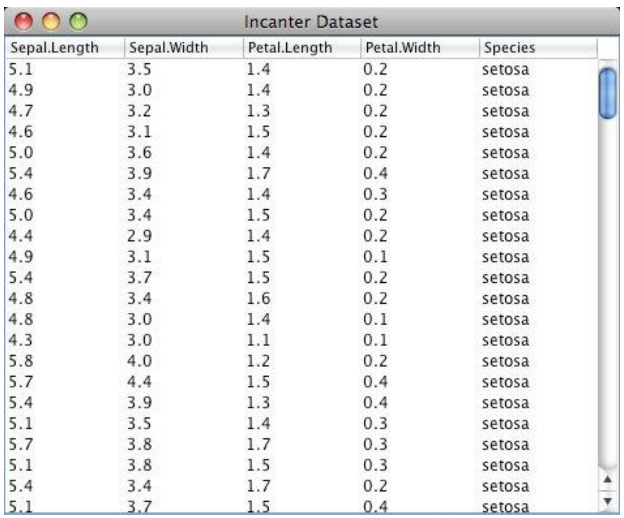
Since the early days of pattern recognition it has been known that the variability and richness of natural data, be it speech, glyphs, or other types of patterns, make it almost impossible to build an accurate recognition system entirely by hand. Consequently, most pattern recognition systems are built using a combination of automatic learning techniques and hand-crafted algorithms. The usual method of recognizing individual patterns consists in dividing the system into two main modules shown in figure 1. The first module, called the feature extractor, transforms the input patterns so that they can be represented by low-dimensional vectors or short strings of symbols that (a) can be easily matched or compared, and (b) are relatively invariant with respect to transformations and distortions of the input patterns that do not change their nature. The feature extractor contains most of the prior knowledge and is rather specific to the task. It is also the focus of most of the design effort, because it is often entirely hand-crafted. The classifier, on the other hand, is often general-purpose and trainable. One of the main problems with this approach is that the recognition accuracy is largely determined by the ability of the designer to come up with an appropriate set of features. This turns out to be a daunting task which, unfortunately, must be redone for each new problem. A large amount of the pattern recognition literature is devoted to describing and comparing the relative

Outline

- Gradient-Based ML ✓
- Convolutional Neural Networks (→ later)
- Comparison with other Methods
- Multi-Module Systems & Graph Transformer Networks
- Multiple Object Recognition & Heuristic Oversegmentation
- Space Displacement Neural Networks
- GTN's as General Transducers
- On-Line Handwriting Recognition System
- Check Reading System

Standard and sequential supervised learning

Supervised Learning



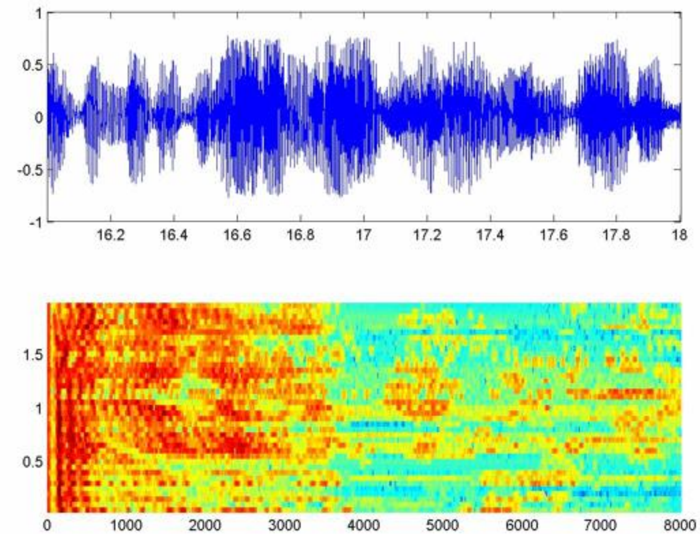
Incanter Dataset

Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
5.1	3.5	1.4	0.2	setosa
4.9	3.0	1.4	0.2	setosa
4.7	3.2	1.3	0.2	setosa
4.6	3.1	1.5	0.2	setosa
5.0	3.6	1.4	0.2	setosa
5.4	3.9	1.7	0.4	setosa
4.6	3.4	1.4	0.3	setosa
5.0	3.4	1.5	0.2	setosa
4.4	2.9	1.4	0.2	setosa
4.9	3.1	1.5	0.1	setosa
5.4	3.7	1.5	0.2	setosa
4.8	3.4	1.6	0.2	setosa
4.8	3.0	1.4	0.1	setosa
4.3	3.0	1.1	0.1	setosa
5.8	4.0	1.2	0.2	setosa
5.7	4.4	1.5	0.4	setosa
5.4	3.9	1.3	0.4	setosa
5.1	3.5	1.4	0.3	setosa
5.7	3.8	1.7	0.3	setosa
5.1	3.8	1.5	0.3	setosa
5.4	3.4	1.7	0.2	setosa
5.1	3.7	1.5	0.4	setosa

feature vectors labels

Typical assumption on data:
- i.i.d.
- Surrounding tasks deemed simple(r)

Sequential Supervised Learning



Typical assumptions on data:
- Sequence information matters
- Overall task has many challenging components (e.g., segmentation → recognition → sequence assembly)

Approaches to classifying sequential data

«A bird in the hand…» approach

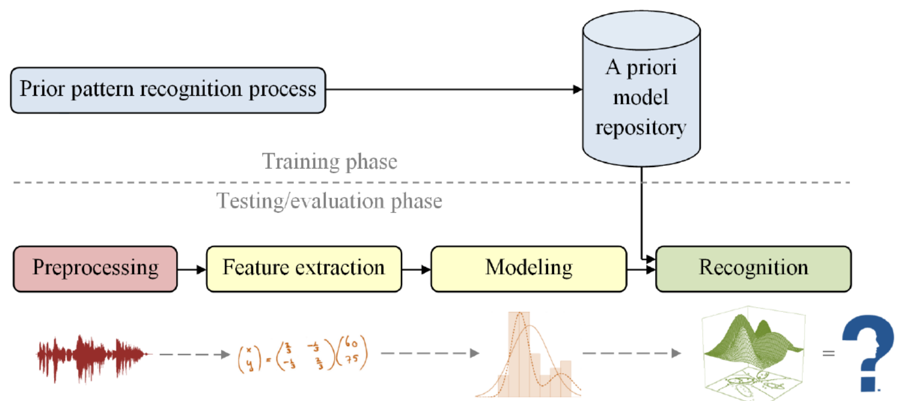
- Train standard classifier, extend it using a sliding window and post-processing (e.g., smoothing)

Direct modeling approach

- Train a generative (statistical) model of the sequence generation process (e.g., HMM)

«…two in the bush» approach

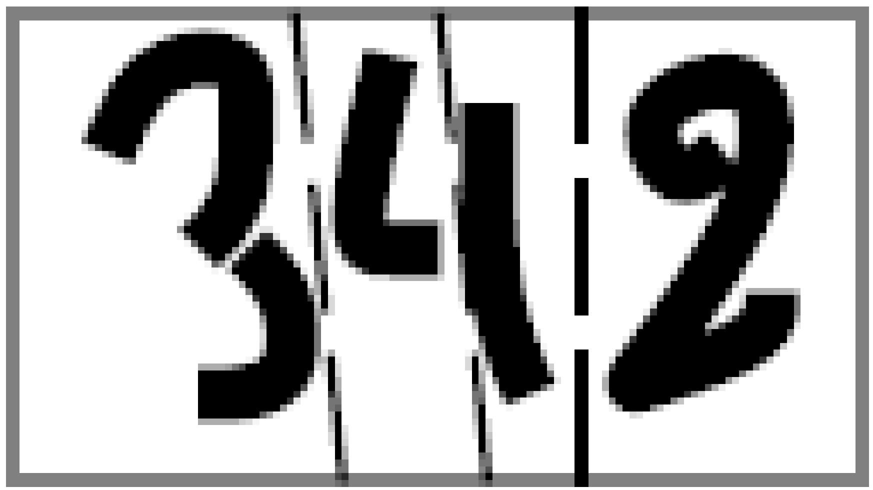
- Build a unified pattern recognition processing chain, optimize it globally with a unique criterion



See also: T.G. Dietterich, «Machine Learning for Sequential Data – A Review», 2002

Proposed Solution: Global Learning
Example: Reading handwritten strings

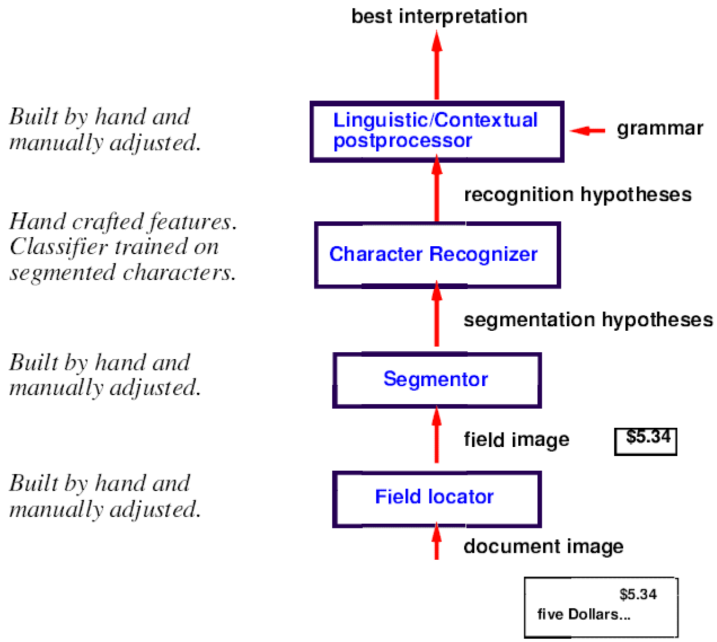
Challenge
- Identify correct character string (*«342»*) on a piece of paper
- Therefore: Find correct segmentation & recognize individual characters



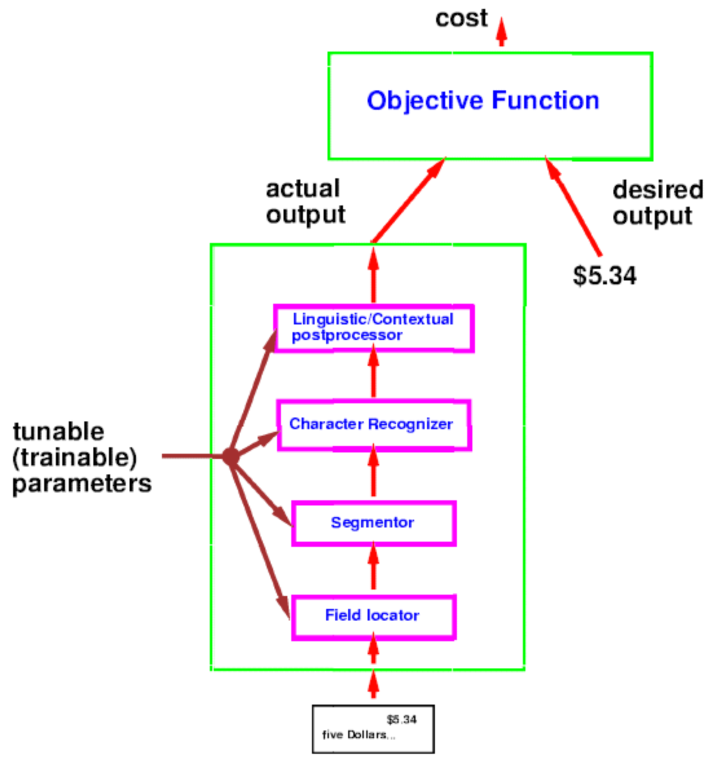
Images sources for this section: → see references slide in appendix

Global Learning
Learning end-to-end

What we know: Traditional pattern recognition system architecture



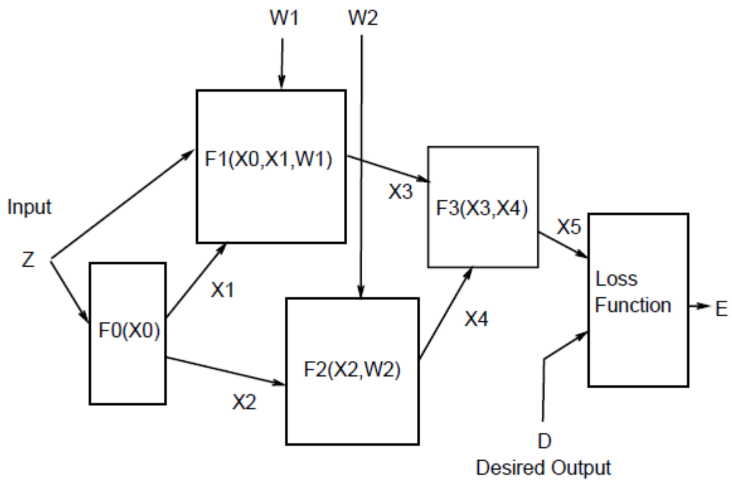
What we want: Train all parameters to optimize a global performance criterion



Foundation: Gradient-based learning

i.e., gradient descent

A trainable system composed of heterogeneous modules:



Backpropagation (bp) can be used if...

- cost (loss) function is differentiable w.r.t. parameters
- modules are differentiable w.r.t. parameters

➔ Gradient-based learning is the unifying concept behind many machine learning methods (→ see day 1 & 5)

➔ Object-oriented design approach: Each module is a class with a `fprop()` and `bprop()` method

Graph transformer network (GTN)

- General architecture for **individual components collectively trainable** via bp
- …using **graph structures** as input and output

➔ See appendix for more details

Conclusions

Less need for manual labeling

- Ground truth only needed for final result (not for every intermediate result like e.g. segmentation)

Early errors can be adjusted later due to…

- …unified training of all pattern recognition modules under one regime
- …postponing hard decisions until the very end

No call upon probability theory for modeling / justification

- Occam's razor: Choose easier discriminative model over generative one
  Vapnik: Don't solve a more complex problem than necessary
- No need for normalization when dealing with "penalties" instead of probabilities → no "other class" examples needed
- Less constrains on system architecture and module selection

Example: Learning to segment without intermediate labels


THE CAVALIER DAILY

Opponents Meet; College Election Details Planned

Gregory To Speak At Coalition Rally

To Convince City

Fair Housing Supporters Plan Rally

Court Ruling Necessitates Draft Re-Evaluation

Council Calls Optional Classes

possible without crop marks?


Gregory To Speak At Coalition Rally

By Tom Jenks
Cavalier Daily Staff Writer

Along with all the events scheduled at the University for April 14, Founder's Day, there will occur an event that has not been posted on any Sesquicentennial calender. On that day, Dick Gregory, noted comedian, speaker, and political aspirant in the last national elections will speak at a rally of the student coalition.

It has not definitely been decided where Mr. Gregory will speak, although the front steps of the Rotunda have been reserved for him. Tentative plans call for him to deliver his speech between 12 and 1:30 in the afternoon. The coalition is also considering Memorial Gym, Cabell Hall Auditorium, and St. Paul's Episcopal Church as possible places for Mr. Gregory to speak.

Charles Murdock, a member of the coalition, contacted Mr. Gregory in Atlanta over Spring Break and asked him if he could speak at the University on April 14. Mr. Gregory said that he could. "I feel that Mr. Gregory's speech will fit in with Founder's Day and its purpose," Mr. Murdock told The Cavalier Daily.

"Counter Sesquicentennial"

Mr. Gregory's speech will be one that he delivers at colleges but is expected to be amended in order to pertain to Jeffersonian principles as he would like to see them applied to the University today. His speech will be part of what the coalition has termed a "Counter Sesquicentennial", the purpose of which will be to point out the faults of the University in the past as well as the need for improvement in the future.

The student coalition is not planning to charge admission to Mr. Gregory's speech, but instead is trying to raise the money to pay by soliciting donations from student organizations.

All proceeds from the donations for Mr. Gregory will be contributed to the Transition Program by the student coalition, who will pass the hat for the Transition Fund at their rally.

Circle-K Society has contributed $200 and is to date the only organization to contribute to the coalition's fund drive, which started Monday.

After meeting Tuesday night to decide whether or not to give money for Mr. Gregory's fee, the University Union announced that it would entirely finance Mr. Gregory on any day other than Founder's Day. The Union also announced that it would donate $200 to the Transition Program.

After a short debate, it was decided by the coalition that it was important to the "Counter Sesquicentennial" (which emphasizes "150 Years of Racism") that Dick Gregory speak on Founder's Day, and the coalition turned down the University Union's offer.

Following the student coalition's rally on April 14, a coalition sponsored boycott of the Sesquicentennial celebration is planned. At approxiamently 2 p.m. after the rally, the coalition and its supporters are to gather on the sides of the Lawn and, wearing black armbands and carrying signs, are to stand in silent boycott of the Sesquicentennial celebration, as the honors procession passes by.

Several members of the coalition expressed the opinion that many students in the procession, who sympathize with the coalition, will drop out of the procession and join them around the Lawn.

"Counter Symposium"

Either during or immediately after the sesquicentennial celebration in Cabell Hall, the coalition will hold a "Counter Symposium", at which Frank Joyce, the director of People Against Racism, will speak and answer questions about the specific issues at the University today.

In addition to the "Counter Symposium", coalition members plan to attend the three scheduled Sesquicentennial symposia on April 14 and plan to be prepared to take part in the discussions.

Review

- ML systems are **pipelines composed of** individual **components** that can be **develope**d **collaboratively** in a team
- Do **ceiling analysis** to **decide which component** in the pipeline is most likely to alter the result for good
- Do **qualitative analysis of wrong**ly predicted **examples** to get **insight** what is going wrong
- Do **numerical error analysis** (i.e., compare CV scores) to **prioritize algorithmic ideas**
- Have a **single performance metric** (e.g., error or F-measure) to **monitor** the **evolution** of your system **continuously**
- Consider **end-to-end training** (global optimization; e.g., GTNs)

P06.2: Applying learning curves

Solve exercise 2 from P06:

- The given Python script draws a learning curve for (any) classifier and certain data sets

- Analyze the performance of the given setup → what insight can you get? What advice as how to proceed would you give?

- Can you also put validation curves to work for you in finding good parameters (see the given library)?

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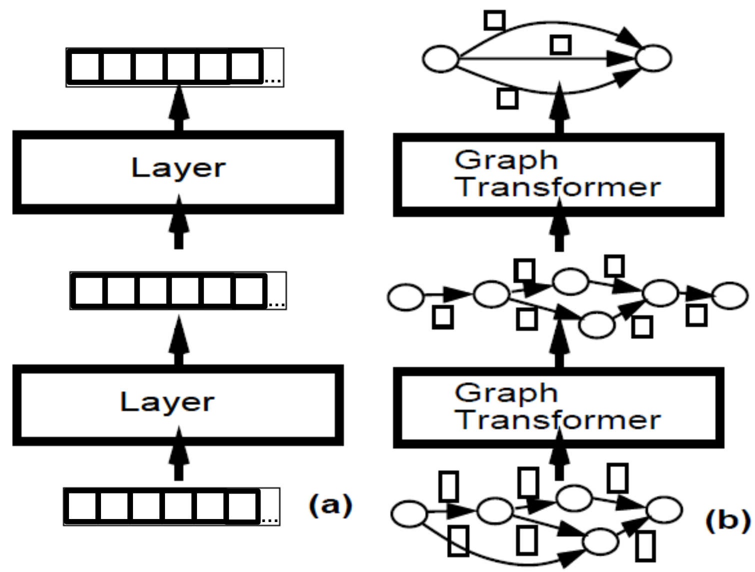
APPENDIX

Graph Transformer Networks

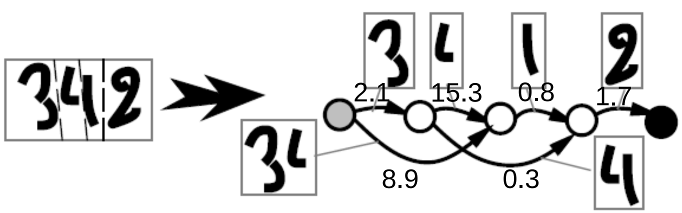
Network of pattern recognition modules that successively refine graph representations of the input

GTNs

- Operate on graphs (b) of the input instead fixed-size vectors (a)



- Graph: DAG with numerical information (“penalties”) at the arcs



➔ GTN takes gradients w.r.t. module parameters and numerical data at input arcs

Example: Heuristic over-segmentation

…for reading handwritten strings

Loss function: Average penalty (over all training data) of best (i.e., lowest penalty) correct path (i.e. associated with correct sequence)

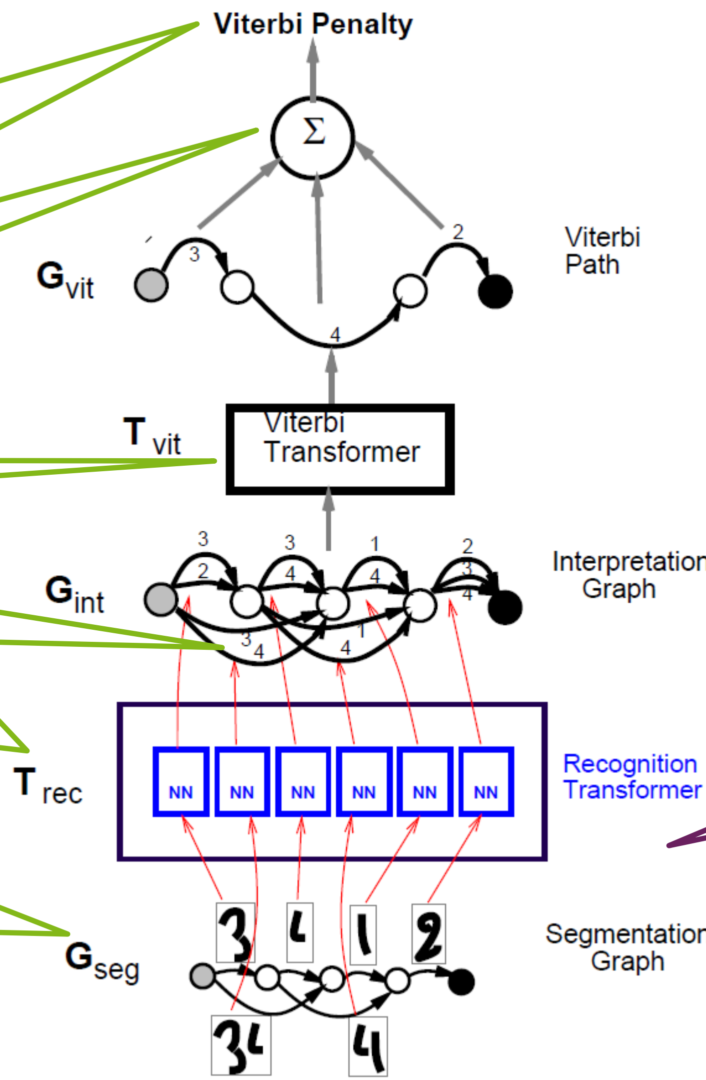
Sum up all penalties

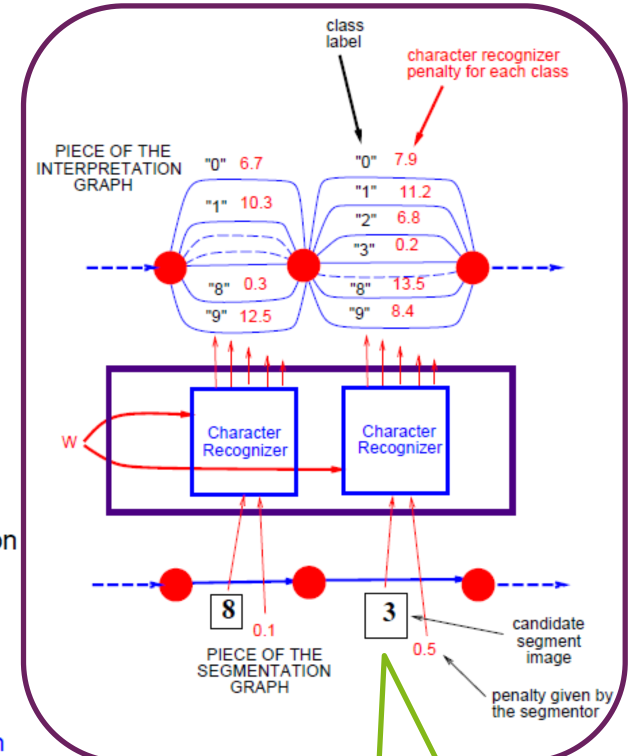
Select path with least cum. penalty

Combined penalties
➔ handled via integrated training

Recognizes individual characters on single images (e.g. CNN)

Contains all possible segmentations (arcs: penalties & images)





For each arc in G_{seg}: Create new one per (character) class, penalty and label attached

Problems:
1. Trivial solution possible (Recognizer ignores input & sets all outputs to small values)
2. Penalty does not take competing answers into account (i.e., ignores training signals)

Solved: Discriminative training builds the class-"separating surfaces rather than modeling individual classes independently of each other" ➔ L=0 if best path is a correct path.

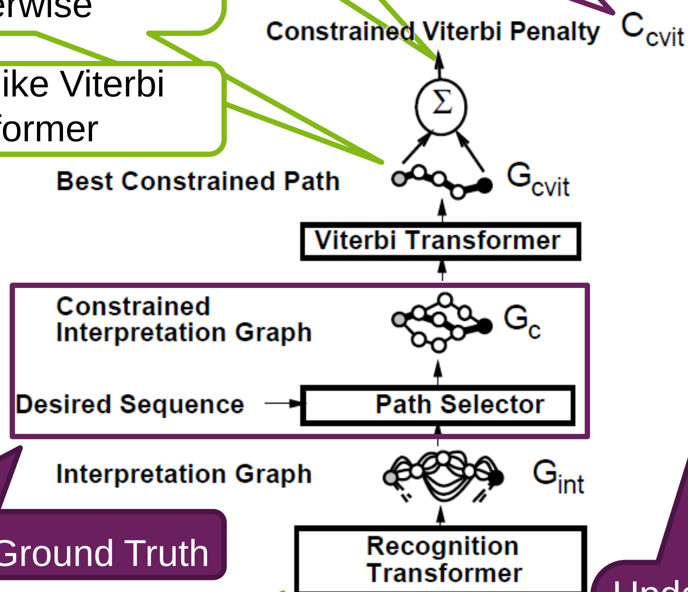
«Viterbi» training

Gradient w.r.t to loss function: 1

Gradient: 1 (for all arcs appearing in Viterbi path), 0 otherwise

Loss function value: $L = C_{cvit}$

Gradient: like Viterbi Transformer

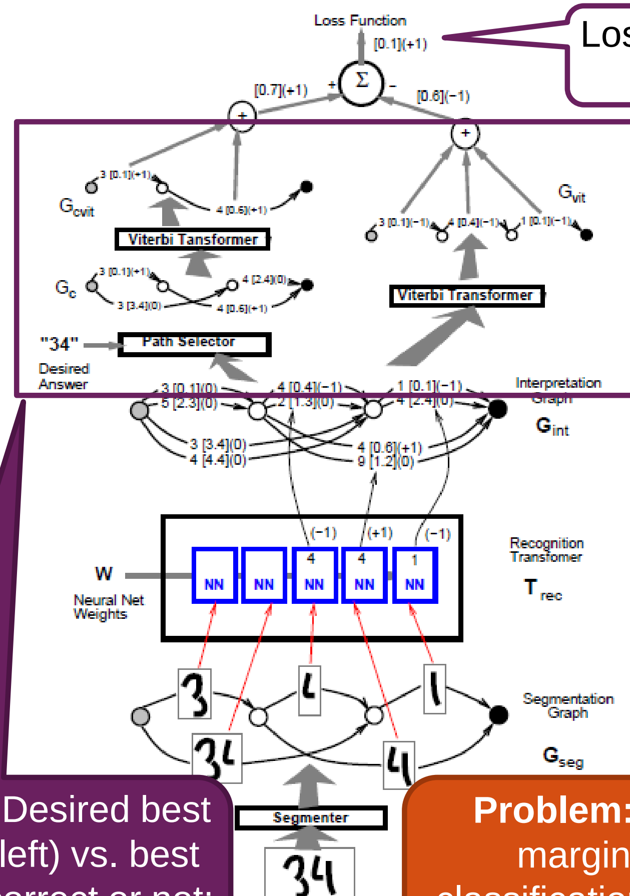


Update: Ground Truth

Gradient: Backprop for NN (one Instance per arc)

Discriminative training

Loss function value: $L = C_{cvit} - C_{vit}$



Update: Desired best output (left) vs. best output (correct or not; right)

Problem: Produces no margin as long as classification is correct (see paper for solution).

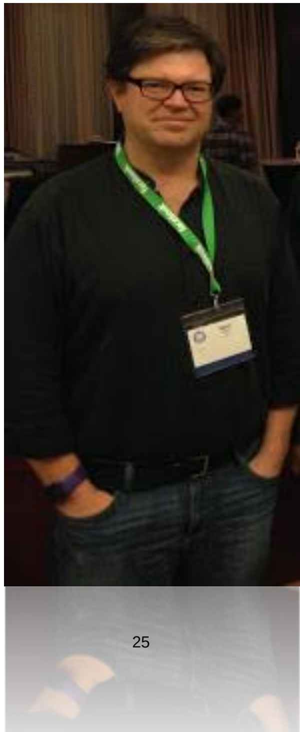
Remarks

Discriminative training

- Uses **all** available training **signals**
- Utilizes “penalties”, **not probabilities**
  ➔ **No** need for **normalization**
  ➔ Enforcing normalization is *“complex, inefficient, time consuming, ill-conditions the loss function”* [according to paper]
- Is the ***easiest/direct* way** to achieve the objective of classification (**as opposed to Generative training**, that solves the more complex density estimation task as an intermediary result)

List of possible GT modules

- All **building blocks of (C)NNs** (layers, nonlinearities etc.)
- **Multiplexer** (though not differentiable w.r.t. to switching input)
  → can be used to dynamically rewire GTN architecture per input
- **min**-function (though not differentiable everywhere)
- **Loss** function



Further Reading

- Original short paper: Bottou, Bengio & LeCun, “Global Training of Document Processing Systems using Graph Transformer Networks”, 1997
  http://www.iro.umontreal.ca/~lisa/pointeurs/bottou-lecun-bengio-97.pdf

- Landmark long paper: LeCun, Bottou, Bengio & Haffner, “Gradient-Based Learning Applied to Document Recognition”, 1998
  http://yann.lecun.com/exdb/publis/pdf/lecun-01a.pdf

- Slide set by the original authors: Bottou, “Graph Transformer Networks”, 2001
  http://leon.bottou.org/talks/gtn

- Overview: Dietterich, “Machine Learning for Sequential Data: A Review”, 2002
  http://eecs.oregonstate.edu/~tgd/publications/mlsd-ssspr.pdf

- Recent work: Collobert, “Deep Learning for Efficient Discriminative Parsing”, 2011
  http://ronan.collobert.com/pub/matos/2011_parsing_aistats.pdf