Welcome to CS523!

- In this course we will:
  - Have fun!
  - Learn about deep learning concepts, techniques, and algorithms.
  - How engineering features shifted to engineering architectures.
  - Real world applications and state-of-the-art.

Course Staff

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In addition to Course Graders

Please let us know ASAP if:

- You are not added to the Piazza course by the end of today.
    - Please use Piazza for all course related communication
    - Please remember that: with great power comes great responsibility

- There is a lecture you cannot attend -> for MT scheduling.

Course Grading

- 5% Piazza Participation
  15% Pre-lecture Material
  30% Problem Sets
  25% Midterm (in-class, TBA)
  25% Project

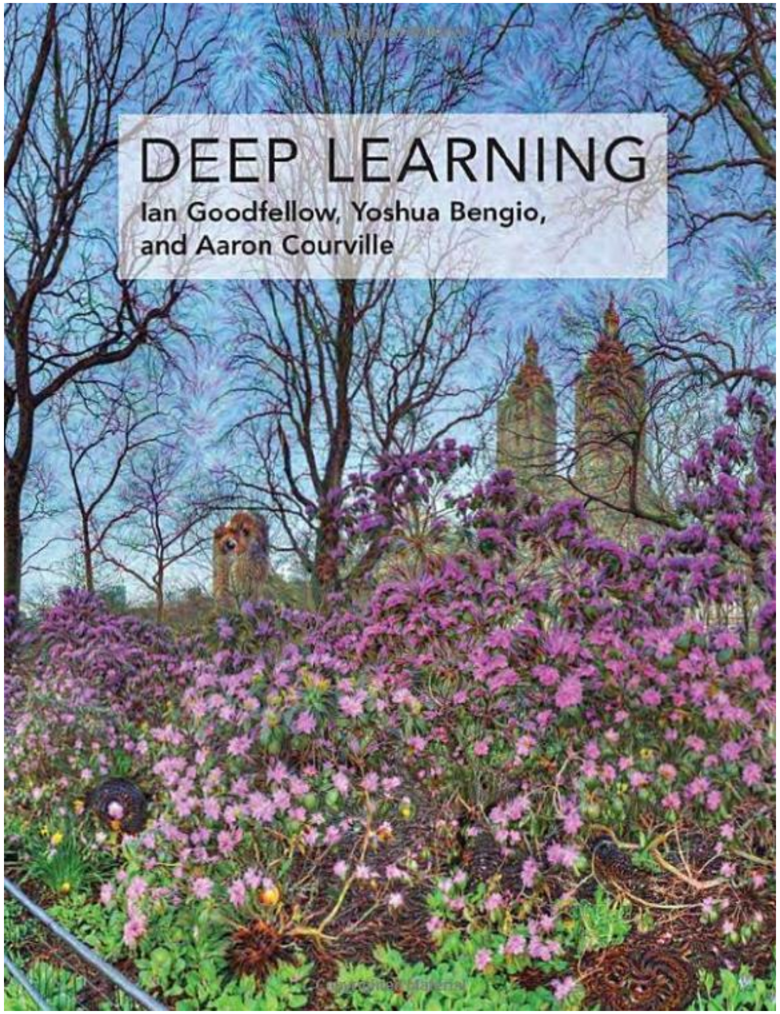
- Late problem sets will be levied a late penalty of 0.5% per hour (up to 48 hours). After 48 hours, no credit will be given.

- All course participants must adhere to the BU Academic Conduct Code:
  http://www.bu.edu/academics/resources/academic-conduct-code/
  All instances of academic misconduct must be reported to the College Academic Conduct Committee.

Course Pre-requisites

- Machine Learning
  - Recursive pre-reqs:
    - Linear algebra (CAS CS 232 or MA 242 or equivalent)
    - Multivariate Calculus (e.g. CAS MA 225)
    - Probability (CAS CS 237 or MA 381 or 581or equivalent)
- Python Programming

Textbook


DEEP LEARNING
Ian Goodfellow, Yoshua Bengio,
and Aaron Courville

Topics

- Machine Learning Review I & II
- Intro to Neural Networks
- Learning in Neural Networks
- Deep Learning Strategies I & II
- Intro to using SCC cluster
- Convolutional Neural Networks
- Recurrent Neural Networks
- Autoencoders
- Attention
- Explainability and Domain Adaptation
- Applications I: Computer Vision
- Applications II: Language and Vision
- Applications III: NLP, Speech and Audio
- Unsupervised Learning
- Fairness and Ethics
- Project Presentations

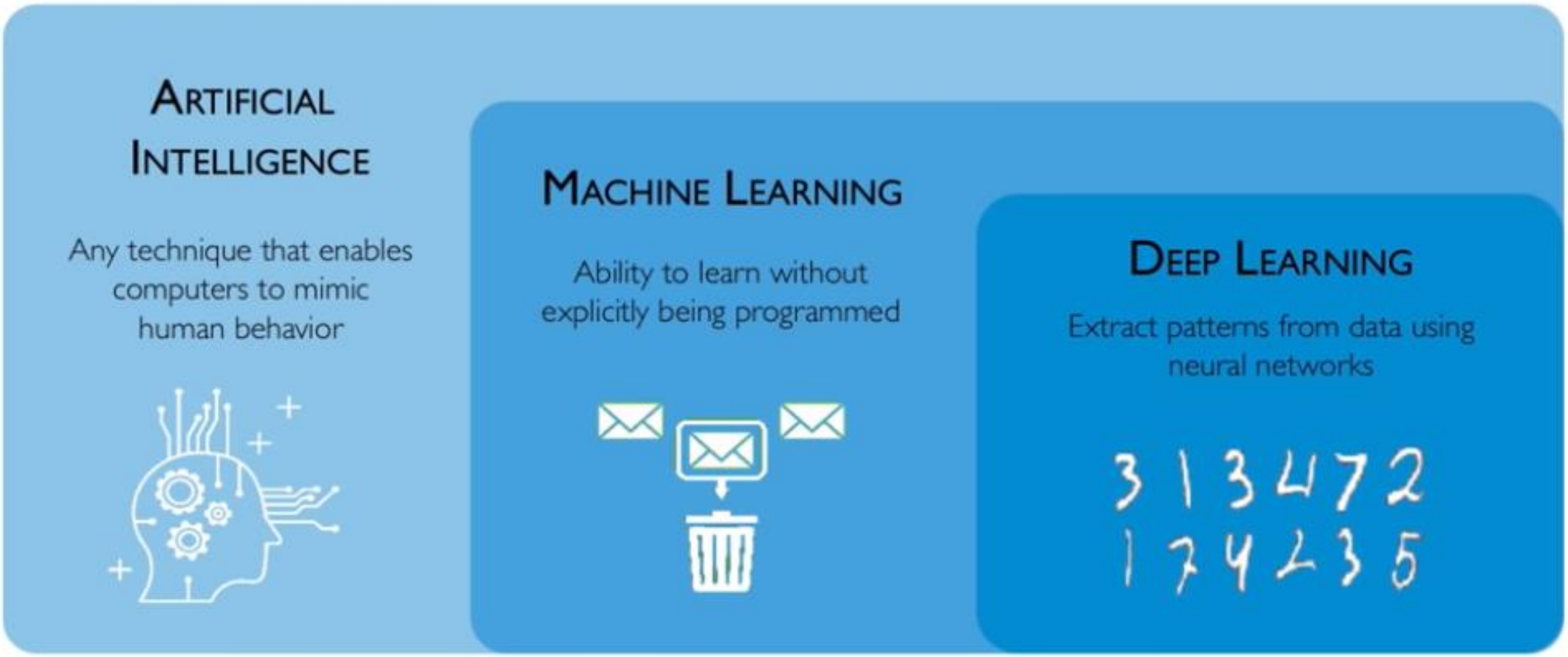
Today: Outline

- **Intro to Deep Learning**
- **Machine Learning Review 1**

- Reminders: …

Neural Networks II

What is Deep Learning?

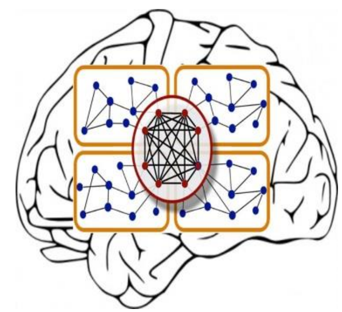


Types of learning

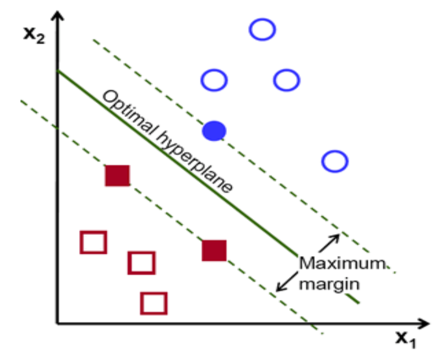
- Supervised
- Unsupervised
- Reinforcement

Machine Learning from Big Data

Artificial Neural Network



Support Vector Machine



Why Deep Learning?

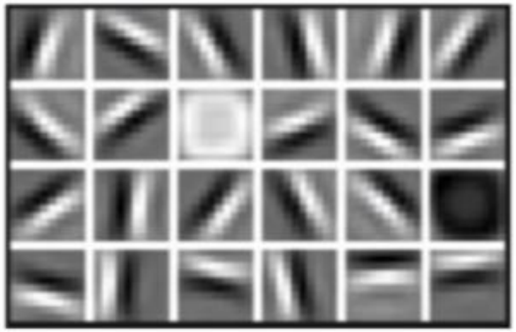
Historically, features were hand-engineered.
Example: Viola and Jones

Why Deep Learning?

Hand engineered features are time consuming, brittle, and not scalable in practice

Can we learn the **underlying features** directly from data?

Low Level Features



Lines & Edges

Mid Level Features

Eyes & Nose & Ears

High Level Features

Facial Structure

Why Now?

- 1952 — Stochastic Gradient Descent
- 1958 — Perceptron
  - Learnable Weights
- ⋮
- 1986 — Backpropagation
  - Multi-Layer Perceptron
- 1995 — Deep Convolutional NN
  - Digit Recognition
- ⋮

Neural Networks date back decades, so why the resurgence?

1. Big Data

- Larger Datasets
- Easier Collection & Storage

IMAGENET

WIKIPEDIA
The Free Encyclopedia

2. Hardware

- Graphics Processing Units (GPUs)
- Massively Parallelizable

3. Software

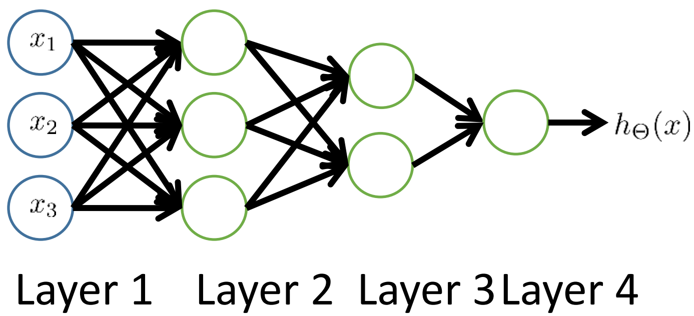
- Improved Techniques
- New Models
- Toolboxes

TensorFlow

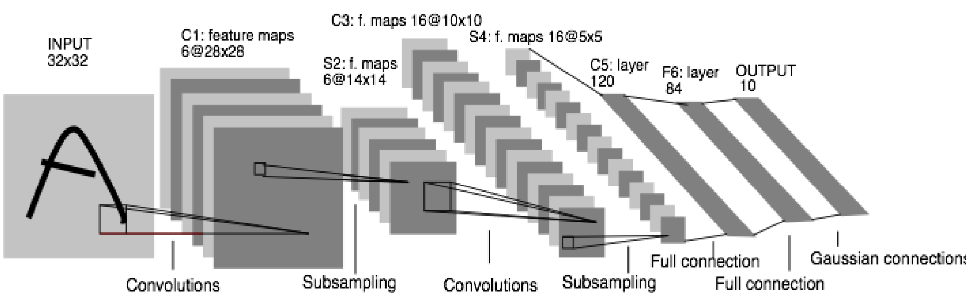
Network architectures

Feed-forward

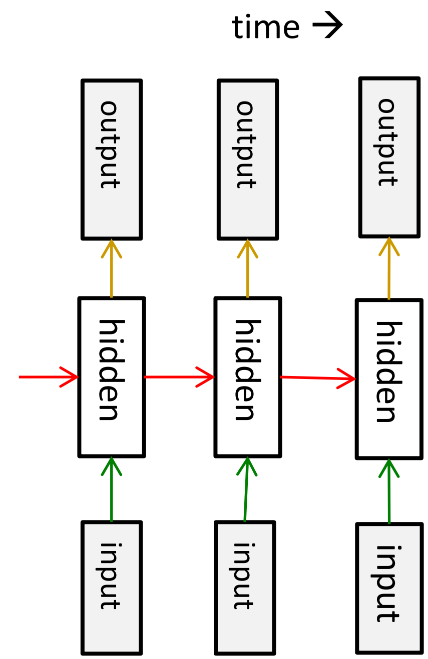
Fully connected

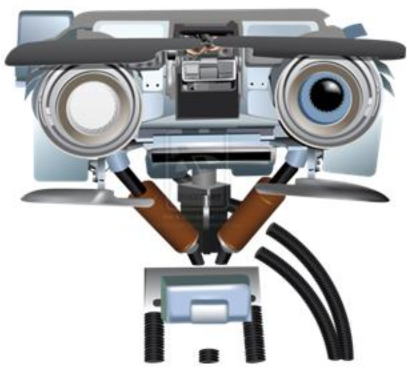


Convolutional



Recurrent





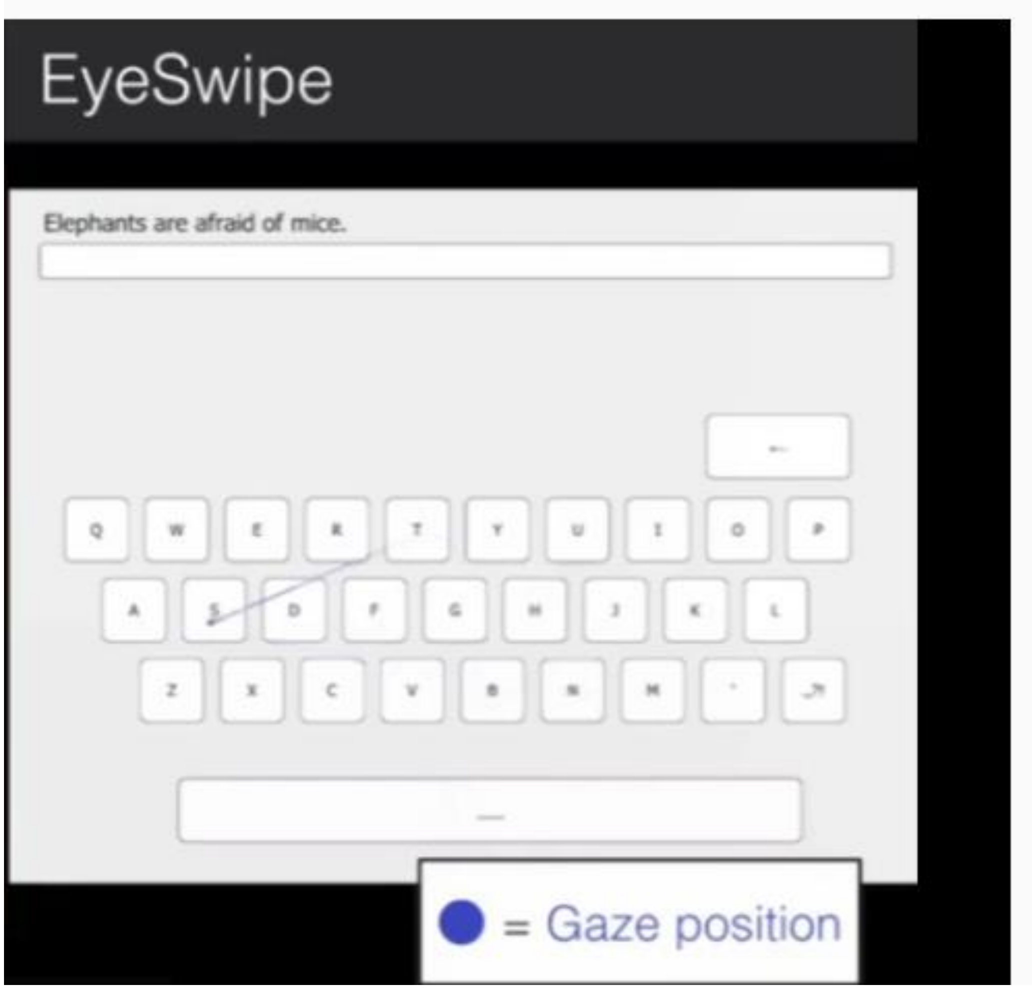
Applications

Camera Mouse

- A program that enables a person with severe disabilities to control the mouse pointer on the computer screen just by moving the head.

http://www.cameramouse.org/about.html

Eye Swipe



A. Kurauchi, W. Feng, A. Joshi, C. Morimoto, M. Betke, EyeSwipe: Dwell-free Text Entry Using Gaze Paths, CHI'16.

Bias Detection

Captioner: A [woman] is mowing lawn.

Captioner's evidence for [woman]:

Fraud Detection

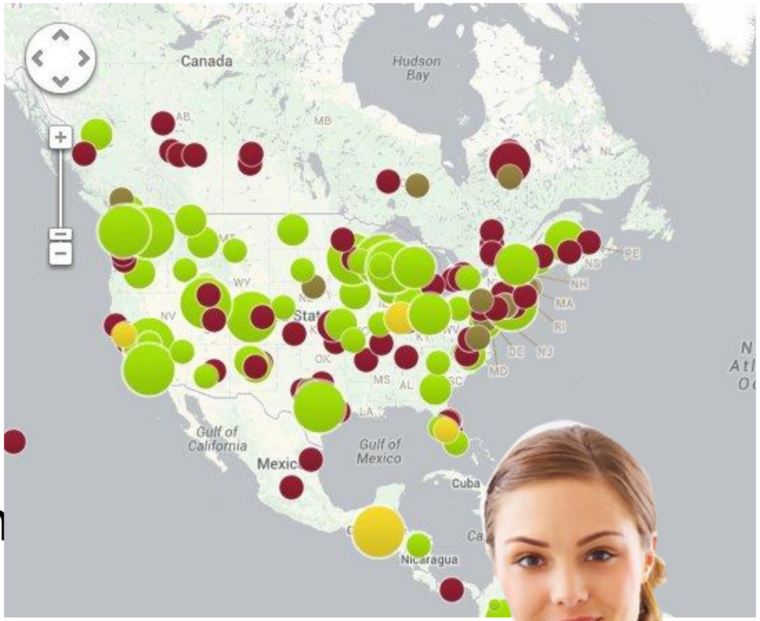
- Fraud detection refers to detection of criminal activities occurring in commercial organizations
  - Malicious users might be the actual customers of the organization or might be posing as a customer (also known as identity theft).
- Types of fraud
  - Credit card fraud
  - Insurance claim fraud
  - Mobile / cell phone fraud
  - Insider trading

- Challenges
  - Fast and accurate real-time detection
  - Misclassification cost is very high

Healthcare Informatics

- Detect anomalous patient records
  - Indicate disease outbreaks, instrumentation errors, etc.
- Key Challenges
  - Only normal labels available
  - Misclassification cost is very high
  - Data can be complex: spatio-temporal

[outbreaks from 2006 to today]() preventable by vaccinations



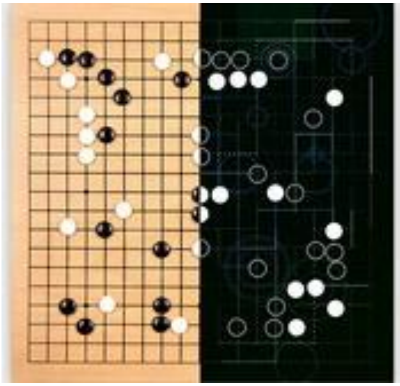
Industrial Damage Detection

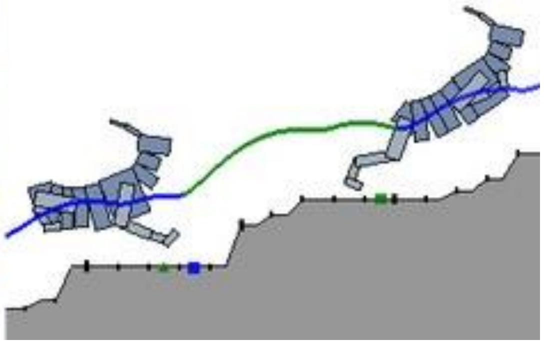
- Industrial damage detection refers to detection of different faults and failures in complex industrial systems, structural damages, intrusions in electronic security systems, suspicious events in video surveillance, abnormal energy consumption, etc.
  - Example: Aircraft Safety
    - Anomalies in engine combustion data

- Key Challenges
  - Data is extremely huge, noisy and unlabelled
  - Most of applications exhibit temporal behavior
  - Detecting anomalous events typically require immediate intervention

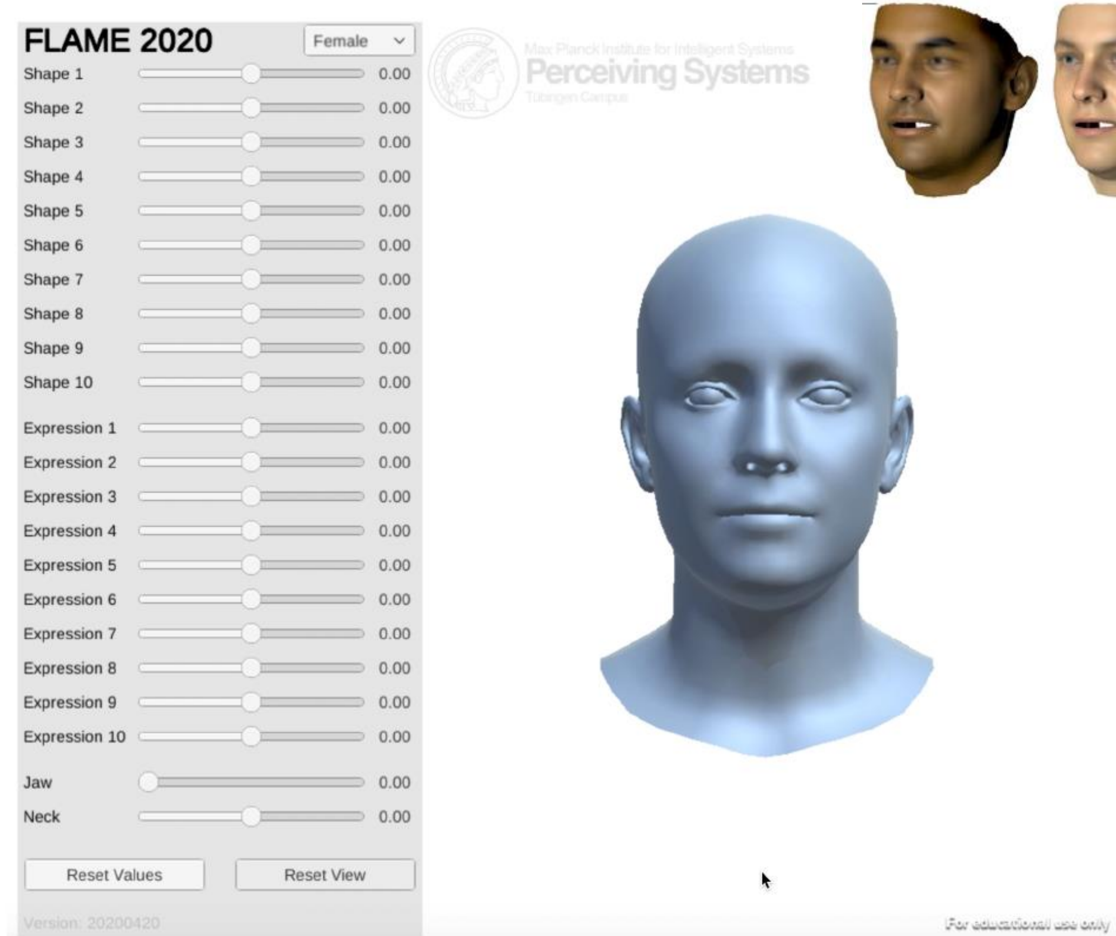
Action Prediction for Agents in Environments

- Current game board layout
- Picture of table with blocks
- Quadruped position and orientation

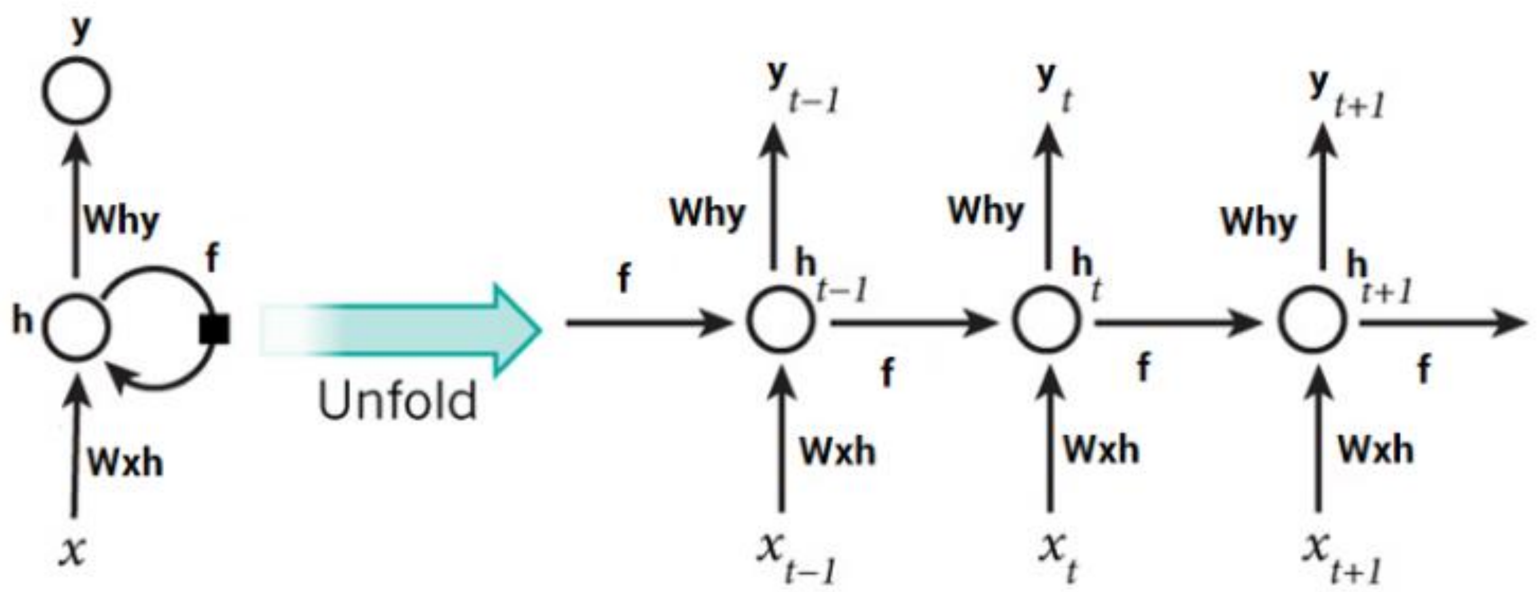




FLAME 3D Morphable Model



Music Generation



https://towardsdatascience.com/generating-music-with-artificial-intelligence-9ce3c9eef806

What if machines understood video content ‘like’ we do?

Applications: Understanding Video Content

AUTONOMOUS VEHICLES

[TechRepublic]

Applications: Understanding Video Content

RETRIEVAL / RECOMMENDATION

[Trans4Mind]

Applications: Understanding Video Content

SURVEILLANCE

[NBCNews]

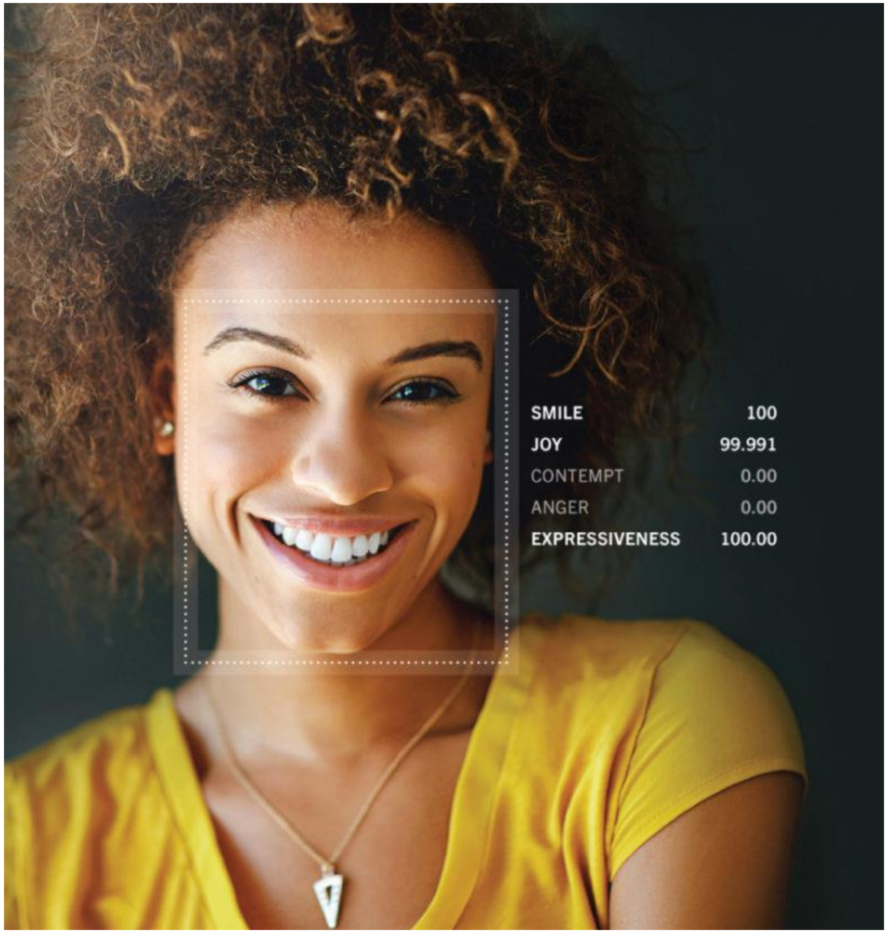
Applications: Understanding Video Content

HUMAN-COMPUTER INTERFACES

[ACM SmartHCI]

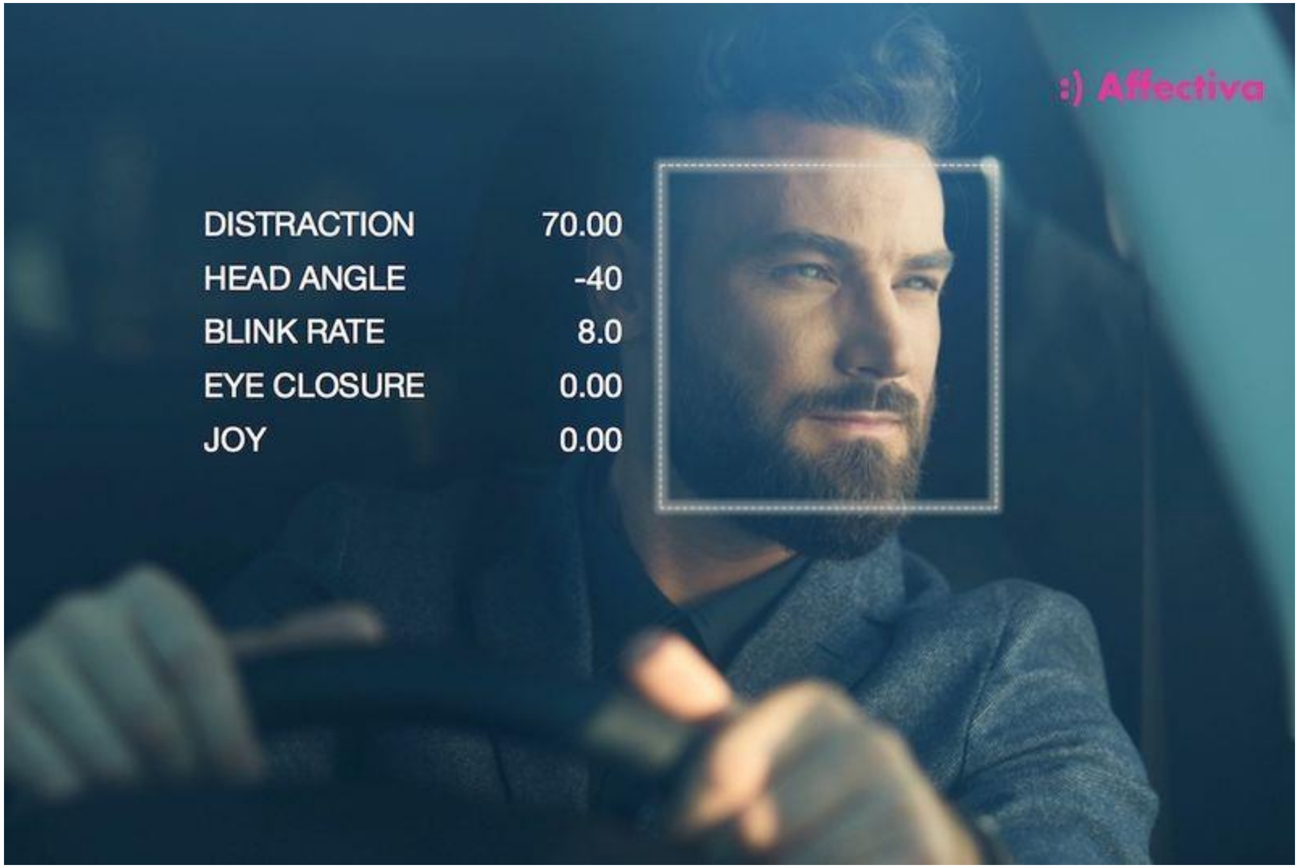
Applications: Understanding Video Content

EMOTIONAL INTELLIGENCE

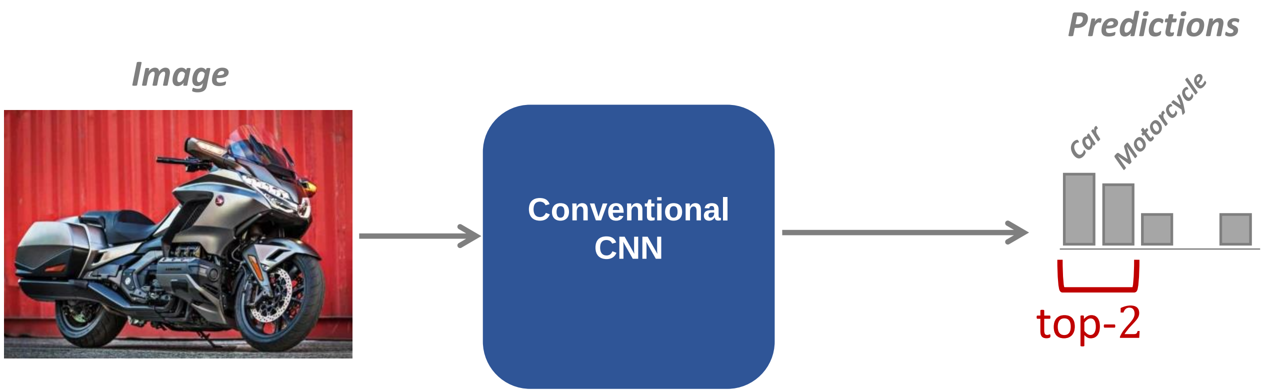


:) Affectiva

Applications: Understanding Video Content



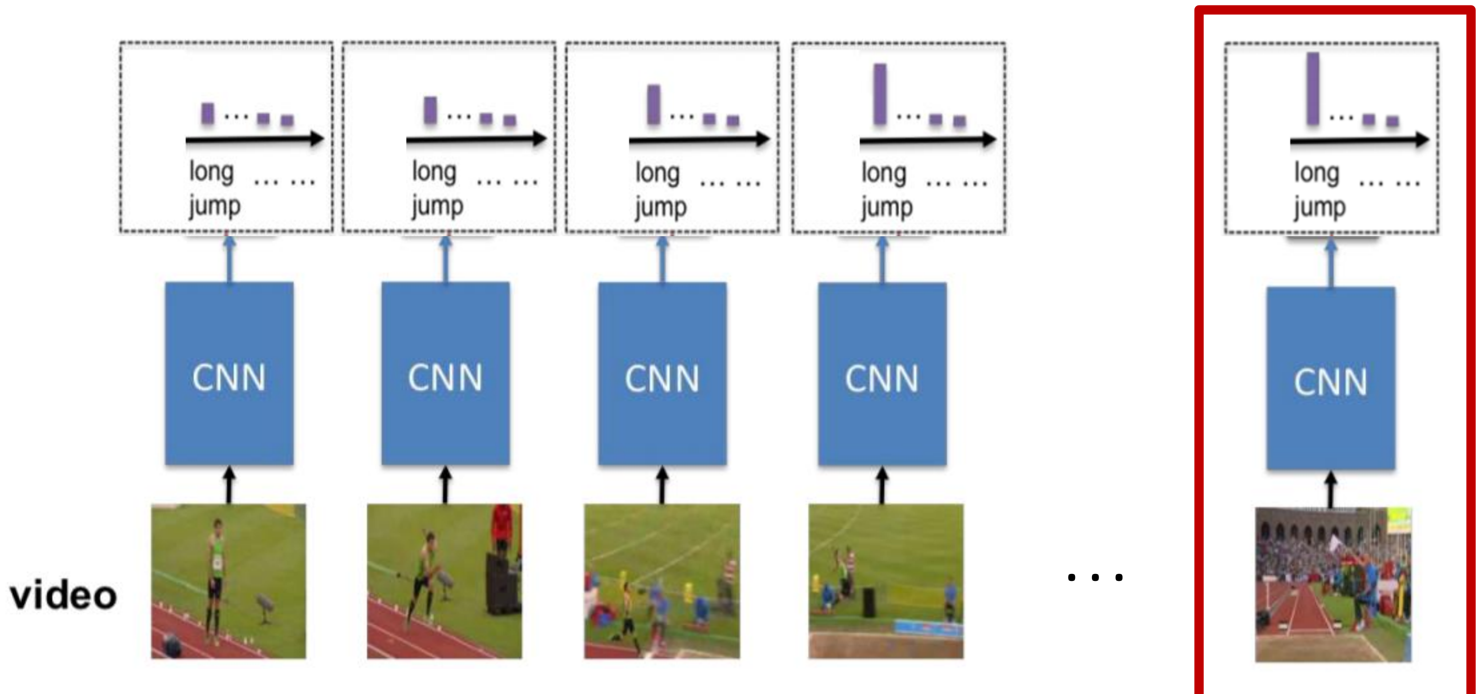
Conventional Deep Classification



Naïve Approach

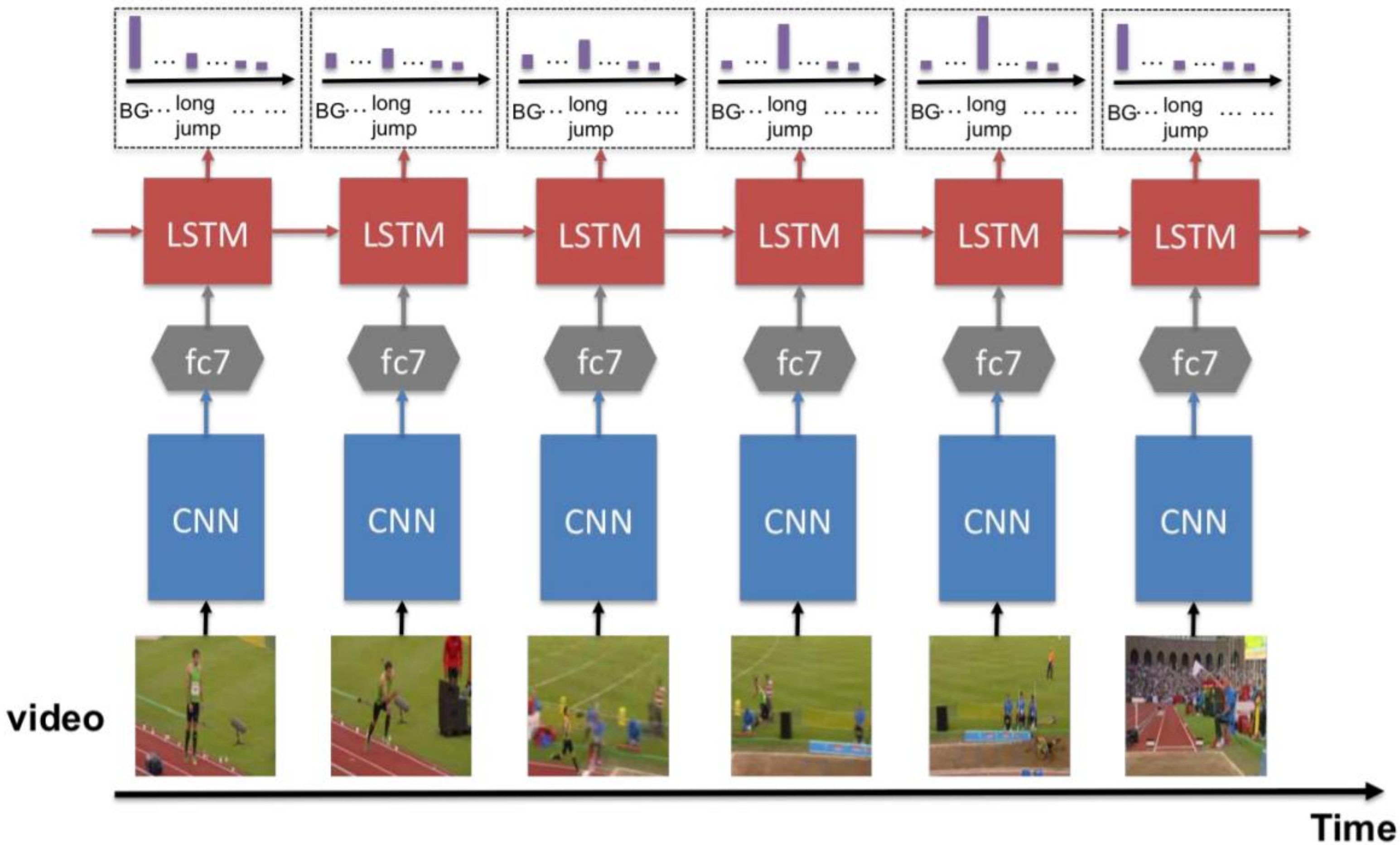
- Treat video frames as still images
- Compute a representation for each frame
- Pool the representations

"A small part of the story"



Modelling History

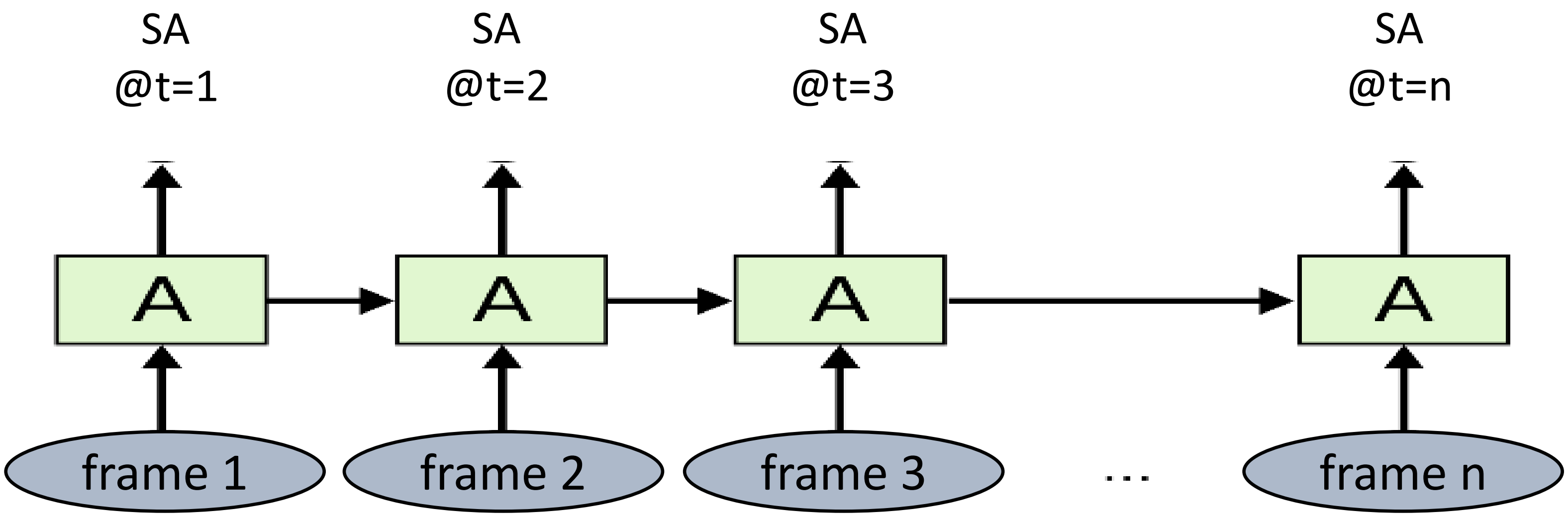
Video Classification



Learning Activity Progression [Ma *et al.*, CVPR'16]

Self-Driving Cars

- SA: steering angle



Application 2: Self-Driving Cars

DeepTesla

DeepTesla, http://selfdrivingcars.mit.edu/deeptesla/

Real-time Applications