Multimedia Event Retrieval

Issues in Analyzing Large Scale User Generated Content

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User Generated Content (UGC) fastest growing open source data

- In 1 month, more video content is uploaded to YouTube than all the US media companies have produced in 60 years.
- YouTube videos are uploaded 100 hours/minute.

- Organization, retrieval, and analysis requires automation and aid from machine learning.

Application: Event Detection

E001 Attempting a board trick

E002 Feeding an animal

E003 Landing a fish

E004 Wedding ceremony

…

E006 Birthday party

E007 Changing a vehicle tire

E008 Flash mob gathering

E009 Getting a vehicle unstuck

E010 Grooming an animal

E011 Making a sandwich

…

E015 Working on a sewing project

…

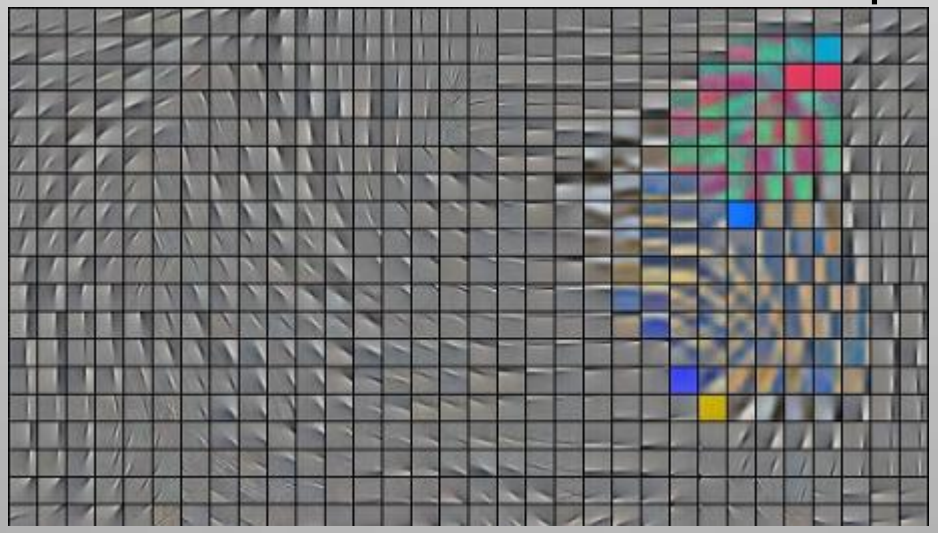
E025 Marriage proposal

E029 Winning a race without a vehicle

E030 Working on a metal crafts project

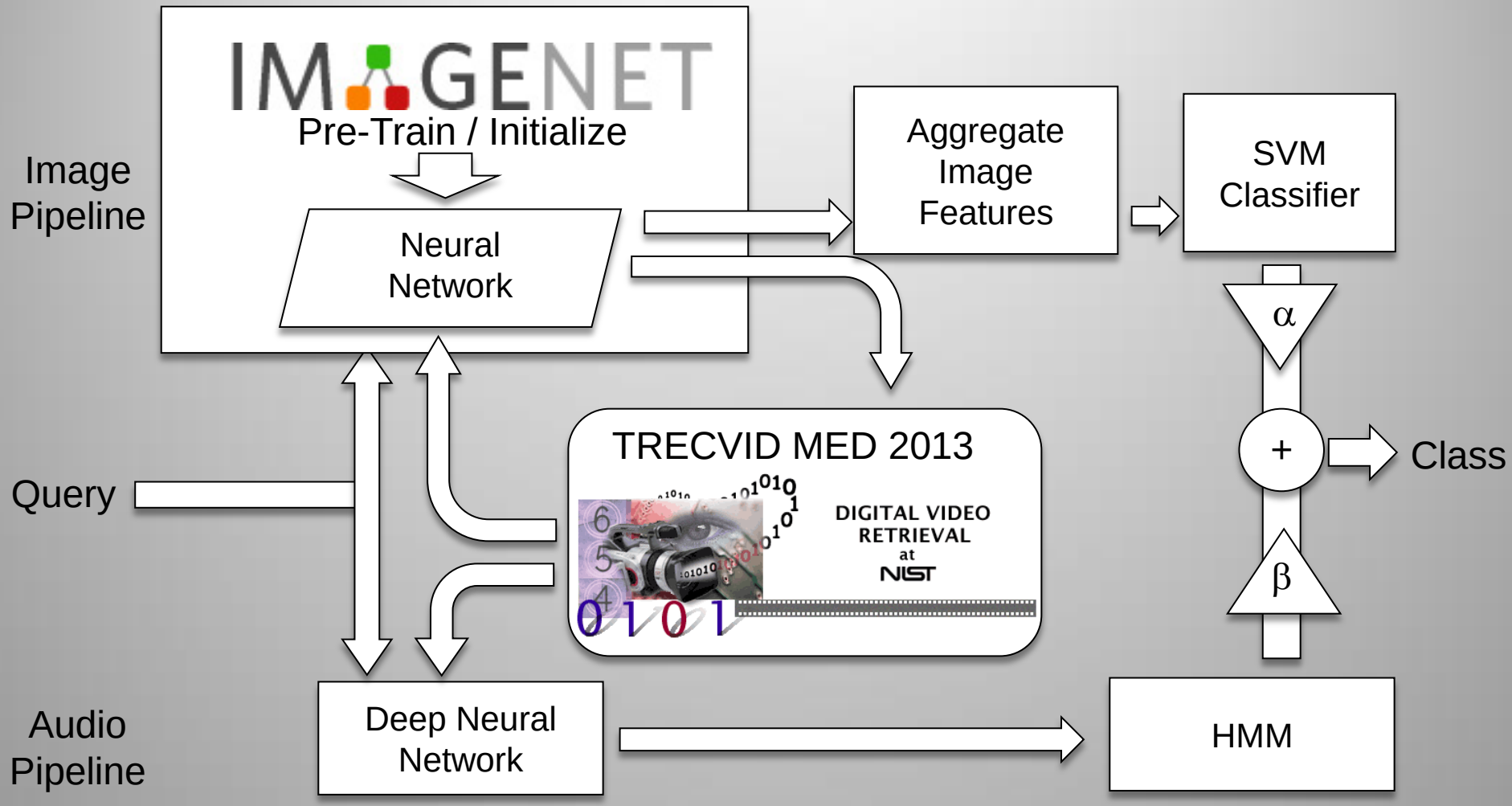
Background: Deep Learning

- To generalize, most ML algorithms add complexity by:
  - Adding more parameters (e.g., manifold learning, GMM's, probabilistic graphical models, etc.)
  - Putting more nonlinear functionality into a linear learner (e.g., SVM's, manifold learning, kPCA, k-Density estimates, etc.)
  - Recently, nonparametrics (e.g., infinite Bayesian models, etc.)
- Mid-2000's movement to do all of that but repeatedly



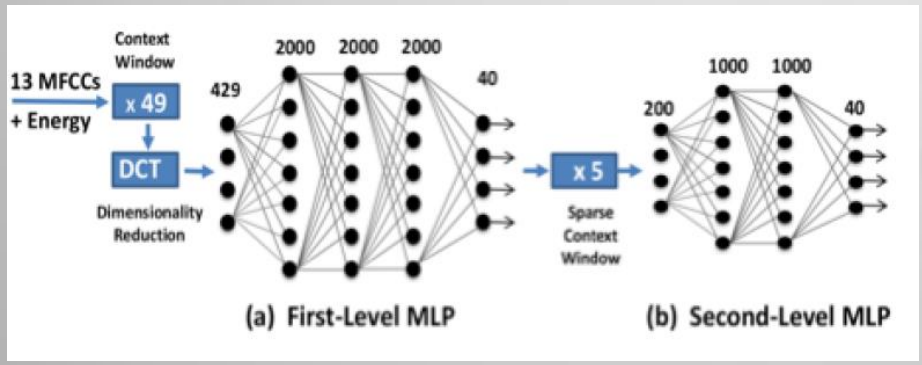
Taken from Ng. et al, '13

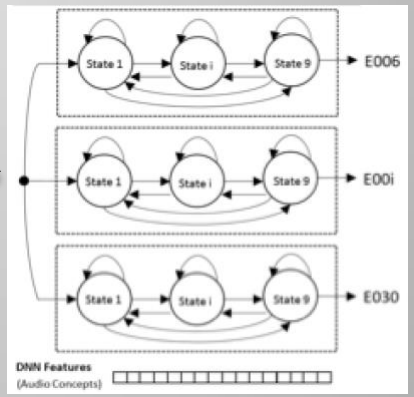
System Description



Audio Classifiers with H-DNN

Audio Deep Neural Network → HMM





- Training based on annotated datasets developed by CMU, SRI, Stanford
- Input MFCC Features + Energy Coefficients
- Two-stage for short-term and long-term predictions
- Temporal consistency improved with HMM models

System Description

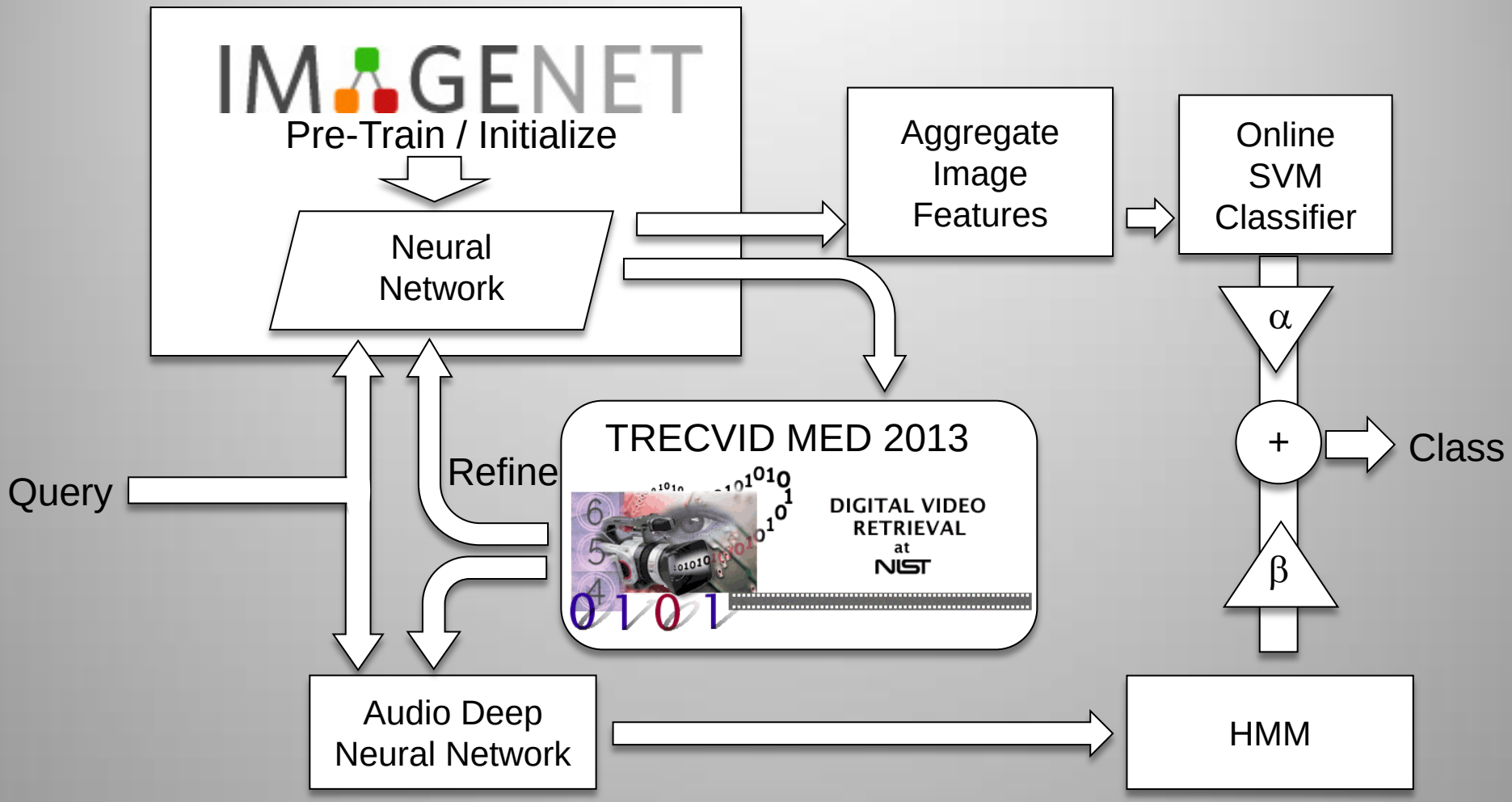
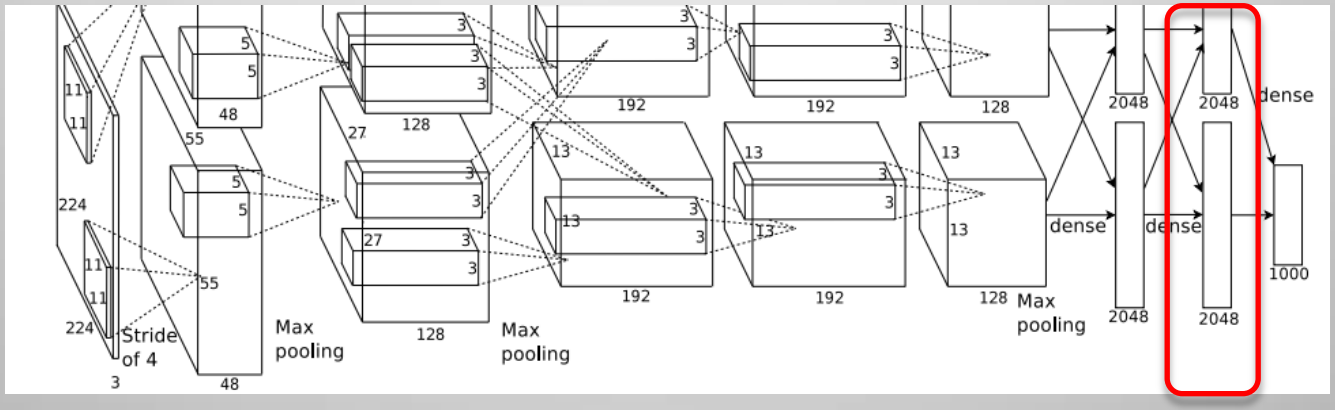


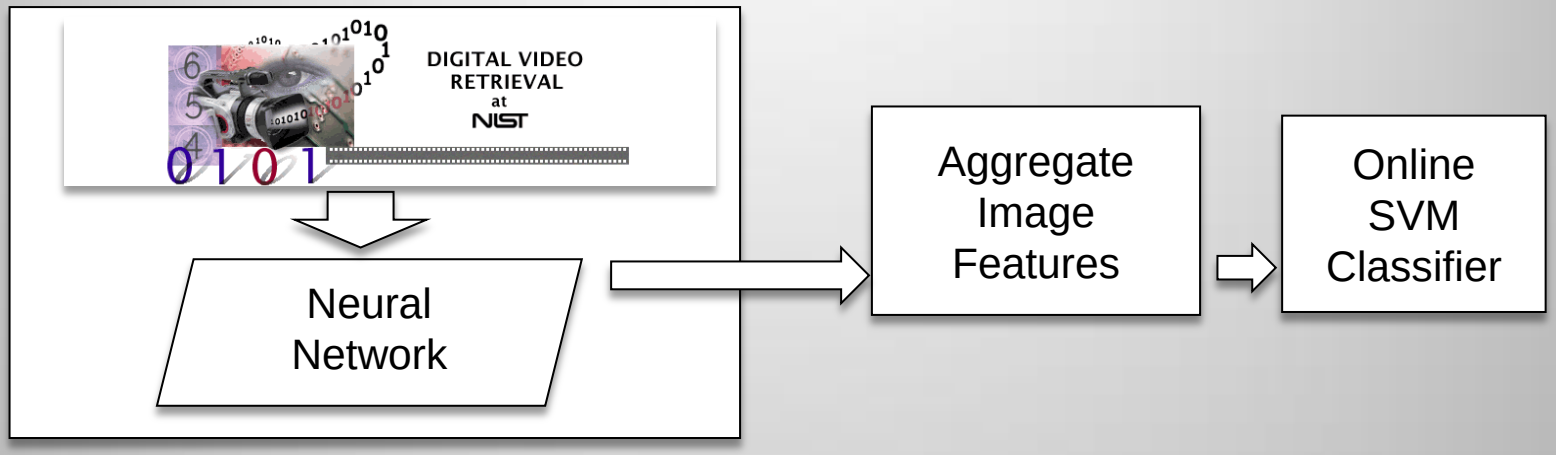
Image Classifiers with D-NN

- ImageNET 2012: Object detection on 1,000 classes
  - Competition winner: Alex Krizhevsky
  - Deep Neural Network Architecture.



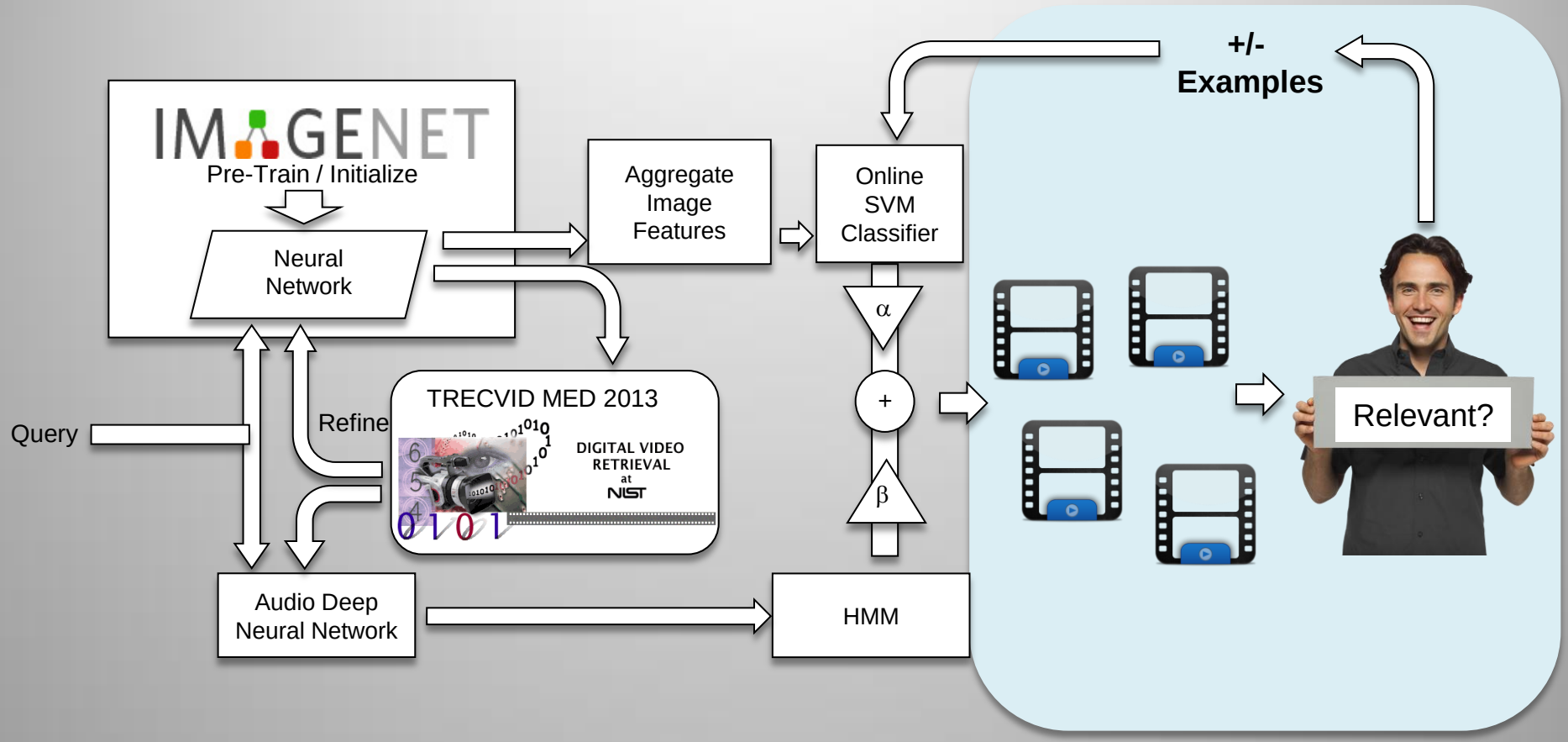
- Image Network will get you close, but…
  - Specifically targeted at nouns and objects
  - Discrete concepts produce a largely noisy result
  - Fewer output options means limited discrimination
  - Effectively make a “hard” decision before the real result

From ImageNET to TRECVid



- Newly tuned TRECVid *image* classifier: apply 2, use 1 layer:
  - L8: Reconstruction ICA Objective Layer: 4096 neurons
  - (Tune L9): Softmax regression layer for multiple instance learning
  - Sigmoid non-linearity (in addition to ReLU) onto L8
- Sum over all frames (L8) to obtain histogram-like features
- Use an SVM Classifier to make the final decision

Classification & Relevance Feedback



Quantitative Comparisons

- Corpora
  - TRECVID-2013 MED Dataset, ~150k Videos from YouTube, Some Hollywood 2 Datasets
- Image Feature-Based Comparisons
  - 8% Improvement Over SIFT-BoW Based Approach [TRECVID MED 13, Competition Results]
- HMM-HDNN Approach
  - 0.68% average precision improvement over MFCC-Based Approach [Elizalde et al]
- Multi-modal Approach
  - 4.23% Improvement over SIFT + MFCC-Based Approach
  - -25.3% based on comparative Amazon Turk classification

The Video LDRD Research Team

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Questions?