Big Visual Data, Deep Learning, and Open Source

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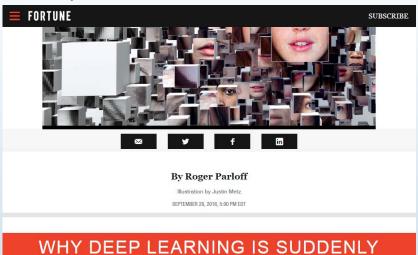


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The Deep Learning Revolution

"Neural nets aren't new. What's changed is that today computer scientists have finally harnessed both the vast computational power and the enormous storehouses of data—images, video, audio, and text files strewn across the Internet—that, it turns out, are essential to making neural nets work well."

Fortune magazine Sep. 28, 2016



CHANGING YOUR LIFE

"Google had two deep-learning projects underway in 2012. Today it is pursuing more than 1,000."

"[Google, Amazon, Microsoft, Apple] all have features that let you search or automatically organize collections of photos with no identifying tags. You can ask to be shown, say, all the ones that have dogs in them, or snow, or even something fairly abstract like hugs."



The (Re-)Birth of Convolutional Neural Networks

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ImageNet Challenge

IM AGENET

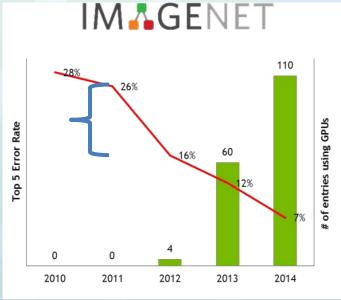
- 1,000 object classes (categories).
- Images:
 - 1.2 M train
 - 100k test.

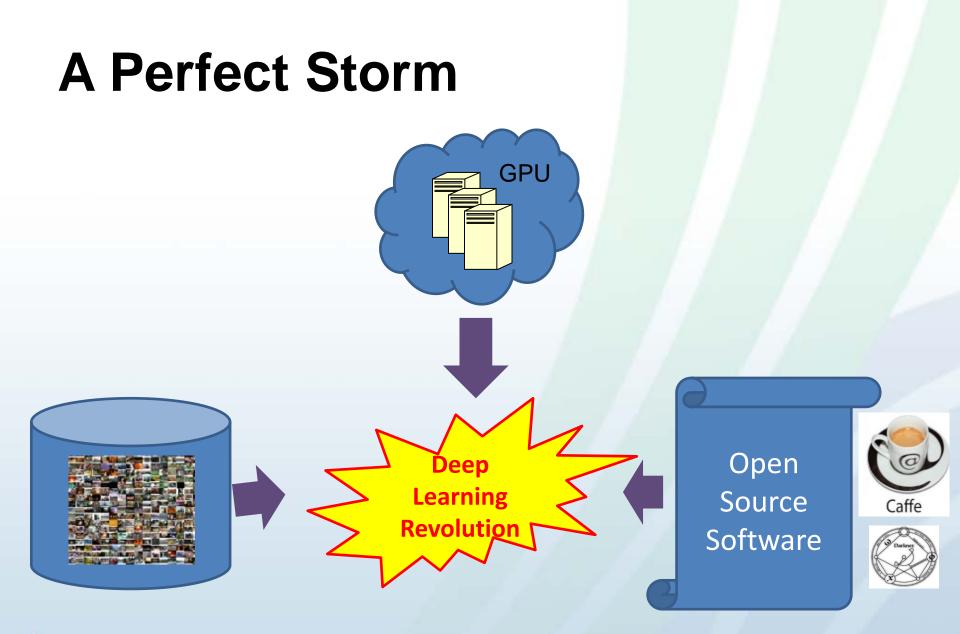
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A. Krizhevsky, I. Sutskever, and G. Hinton. <u>"ImageNet Classification with Deep</u> <u>Convolutional Neural Networks</u>." *Neural Information Processing Symposium*, 2012.

J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li and L. Fei-Fei. **ImageNet: A Large-Scale Hierarchical Image Database.** *IEEE Computer Vision and Pattern Recognition,* 2009.



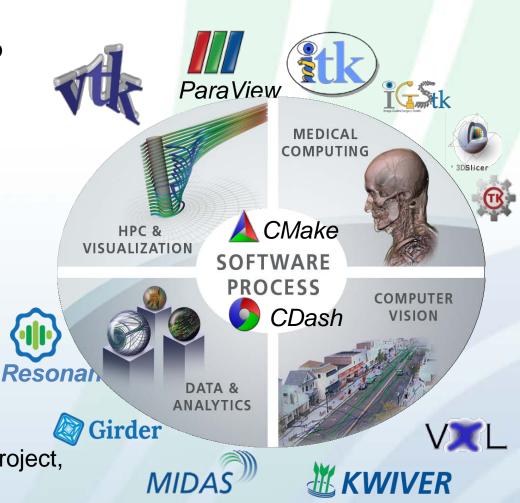




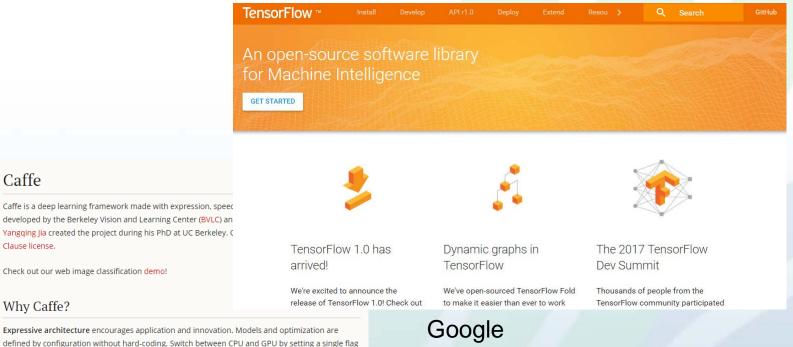
Kitware Open Source Platforms

- KWIVER Kitware Imagery and Video
 Exploitation and Retrieval
- VTK the visualization toolkit
- ParaView large data analysis & visualization application
- **ITK** insight image analysis toolkit
- CMake cross-platform build system
 - CDash, CTest, CPack, software process tools
- Resonant/Girder informatics and information visualization
- Kiwi & VES mobile visualization
- IGSTK, CTK, vxl, Open Chemistry Project, VolView, tubeTk, and more...
- **MIDAS** for computational scientific research, testing, and visualization

ware



CNN Open Source Platforms



defined by configuration without hard-coding. Switch between CPU and GPU by setting a single flag to train on a GPU machine then deploy to commodity clusters or mobile devices.

Extensible code fosters active development. In Caffe's first year, it has been forked by over 1,000 developers and had many significant changes contributed back. Thanks to these contributors the framework tracks the state-of-the-art in both code and models.

Speed makes Caffe perfect for research experiments and industry deployment. Caffe can process over 60M images per day with a single NVIDIA K40 GPU*. That's 1 ms/image for inference and 4 ms/image for learning. We believe that Caffe is the fastest convnet implementation available.

UC Berkeley http://caffe.berkeleyvision.org/ ware

Caffe

by the BVLC

Created by

Yangqing Jia

Lead Developer

Evan Shelhamer

Deep learning framework

View On GitHub

Caffe

Clause license.

Why Caffe?

https://www.tensorflow.org/

CNN Open Source Models

Model Zoo

Iacopo Masi edited this page 16 days ago · 111 revisions

Check out the model zoo documentation for details.

To acquire a model:

- download the model gist by ./scripts/download_model_from_gist.sh <gist_id> <dirname> to load the model metadata, architecture, solver configuration, and so on. (<dirname> is optional and defaults to caffe/models).
- 2. download the model weights by ./scripts/download_model_binary.py <model_dir> where <model_dir> is the gist directory from the first step.

or visit the model zoo documentation for complete instructions.

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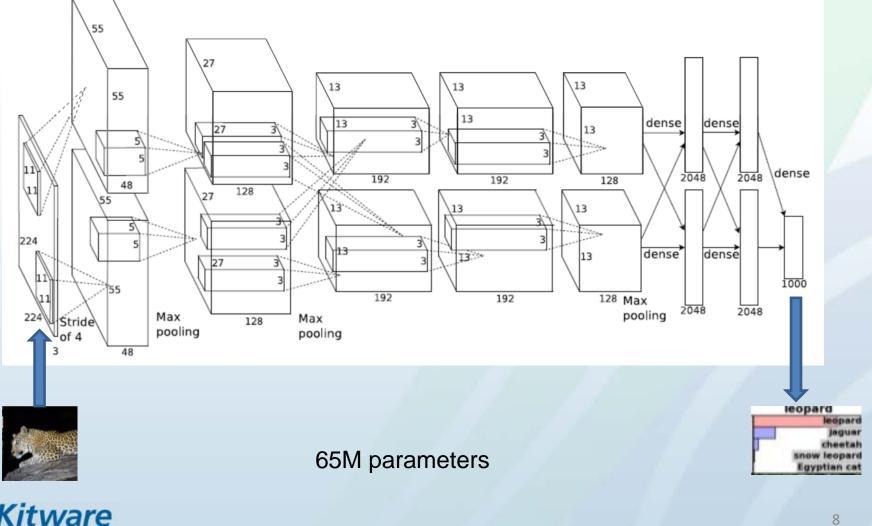
- · Berkeley-trained models
- Network in Network model
- Models from the BMVC-2014 paper "Return of the Devil in the Details: Delving Deep into Convolutional Nets"
- Models used by the VGG team in ILSVRC-2014
- Places-CNN model from MIT.
- GoogLeNet GPU implementation from Princeton.
- Fully Convolutional Networks for Semantic Segmentation (FCNs)

Caffe 41 models

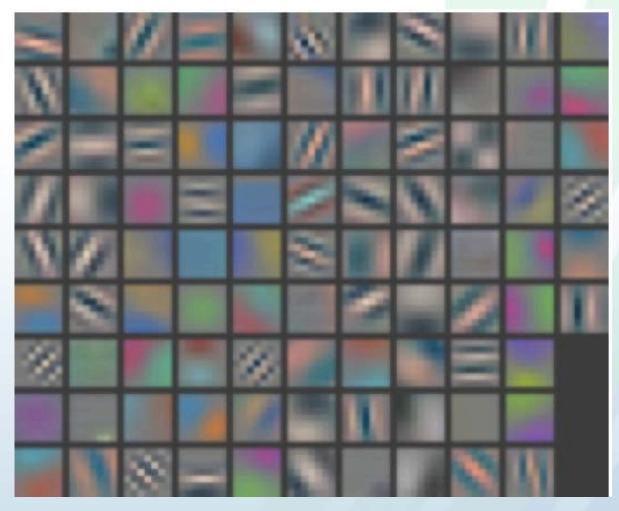


AlexNet

A. Krizhevsky, I. Sutskever, and G. Hinton. "ImageNet Classification with Deep Convolutional Neural Networks." Neural Information Processing Symposium, 2012.



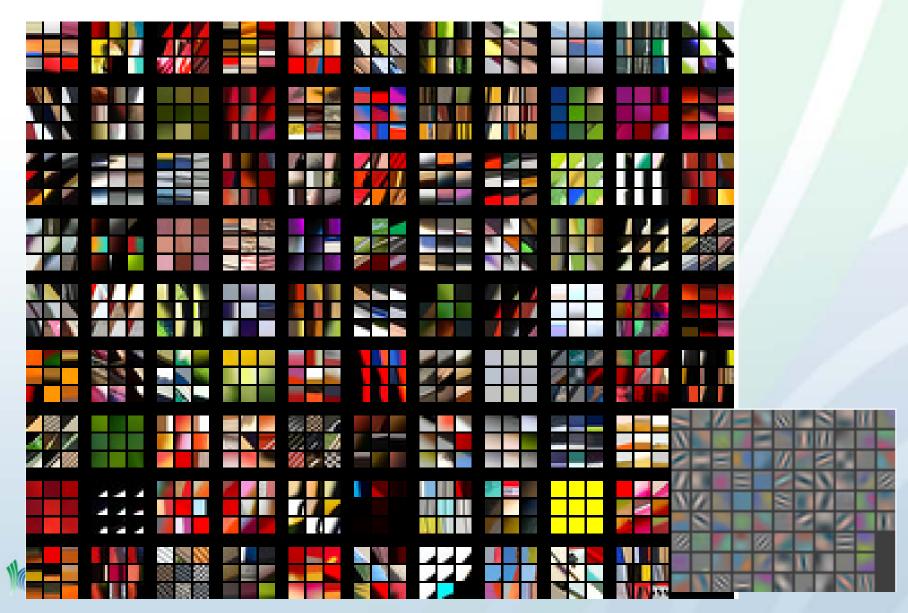
Layer 1 Filters

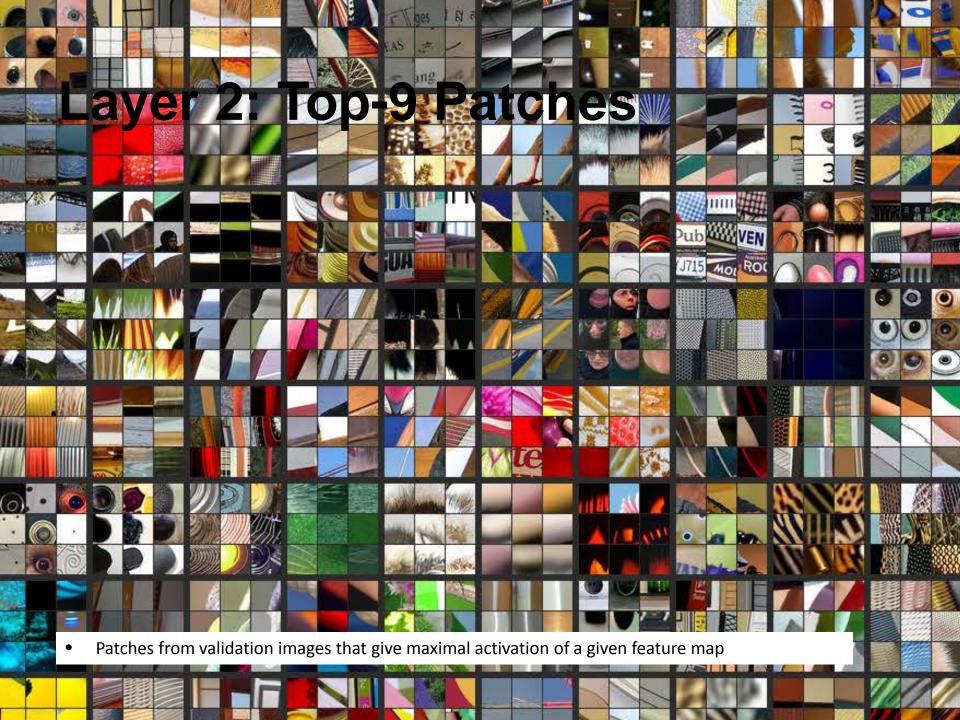


Slide credit: Yann LeCun



Layer 1: Top-9 Patches





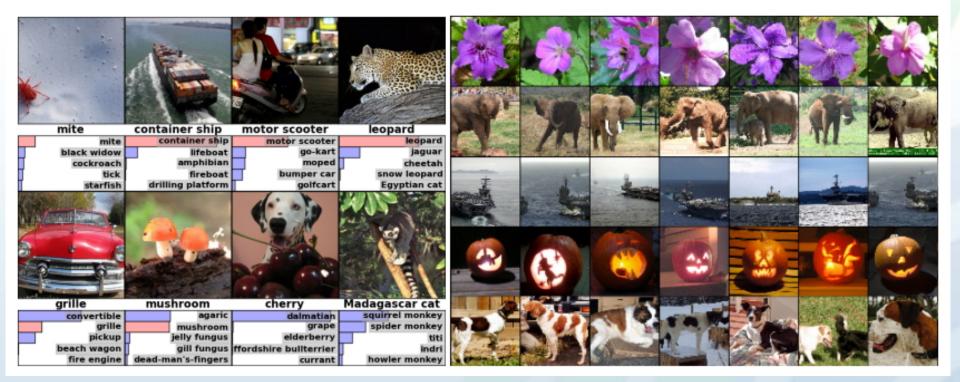
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AlexNet Results



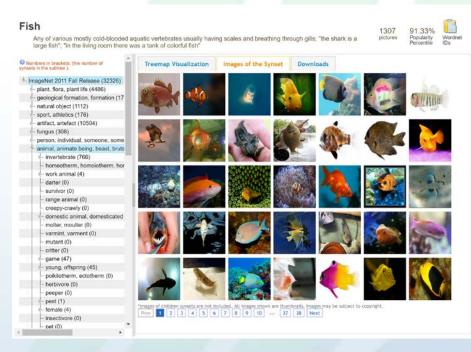
Top 5 Classes

Training Images



Training Deep Networks: ImageNet

- Many deep networks for image recognition are trained on ImageNet
- ImageNet contains a large number of training images with wide diversity
- Using 1M+ images for training is typical
- Days worth of training time
- What can you do if your dataset is different from ImageNet content?
 - Similar datasets do not exist for aerial / overhead / ISR data



14M+ Images 21K+ Categories



Training Alternatives

• Train a network from scratch

 Requires large training volume, significant ground truth, computation time (days), experimental iteration

Refine an existing network

- Still requires potentially large training volume with significant ground truth
- Relies on visual features being similar across datasets open question

Simulation

Nare

- Simulated scenes can provide both training data and labels (known from underlying model)
- Required level of fidelity is unknown

Generative models

- Training process tries to reproduce the input imagery
- Hopefully produces features useful for discrimination

Training deep networks is still an art

Deep Learning Image Descriptors

 AlexNet or any CNN can be used as a generic image descriptor

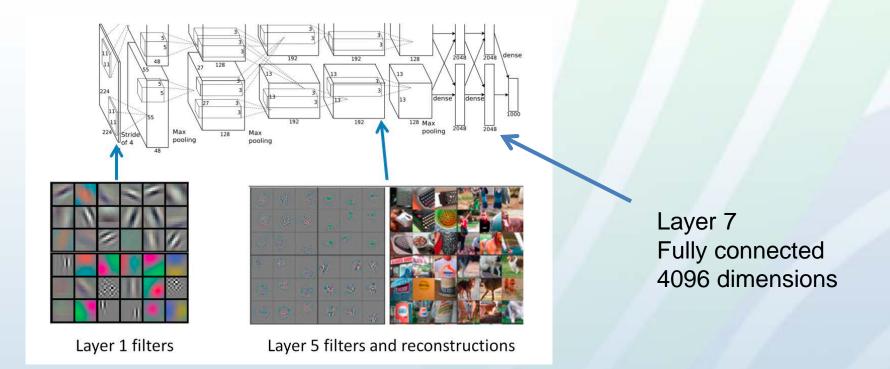




Image Query



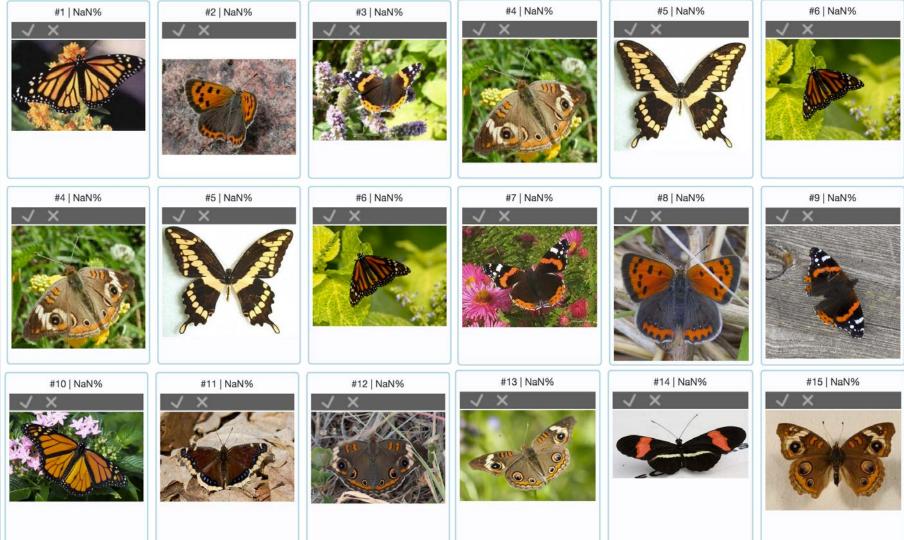
Dataset contains 832 images with 55-100 images per type.

Start IQR with a single positive examplar

Use CAFFE AlexNet Layer 7 as an image descriptor



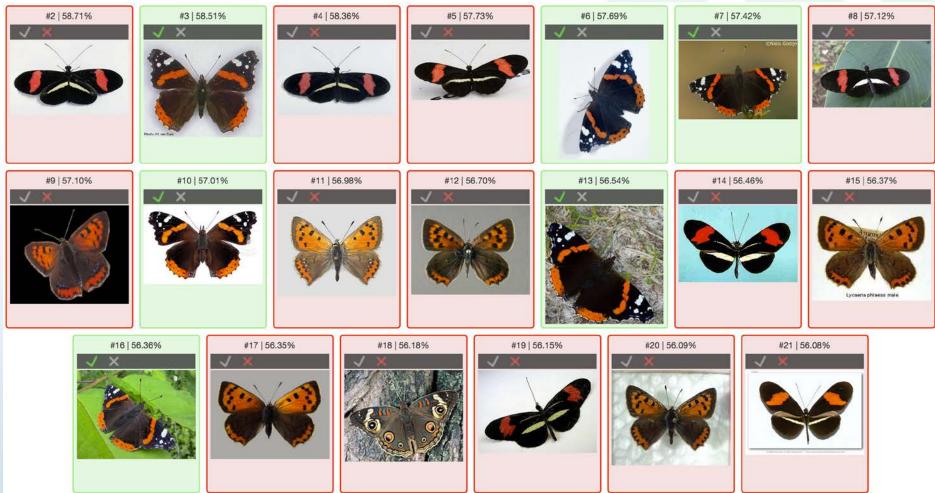
Random Selections from Leeds Butterfly



Kitware

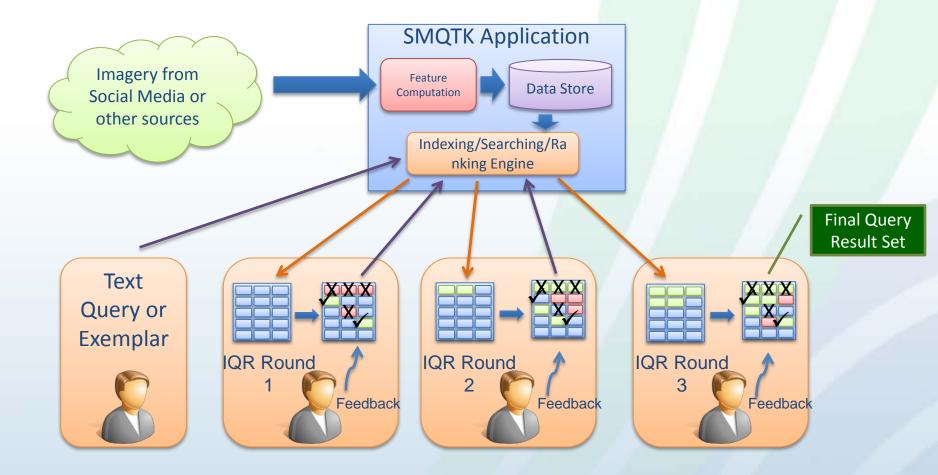
Josiah Wang, Katja Markert, and Mark Everingham Learning Models for Object Recognition from Natural Language Descriptions In Proceedings of the 20th British Machine Vision Conference (BMVC2009)

Results from Single Exemplar



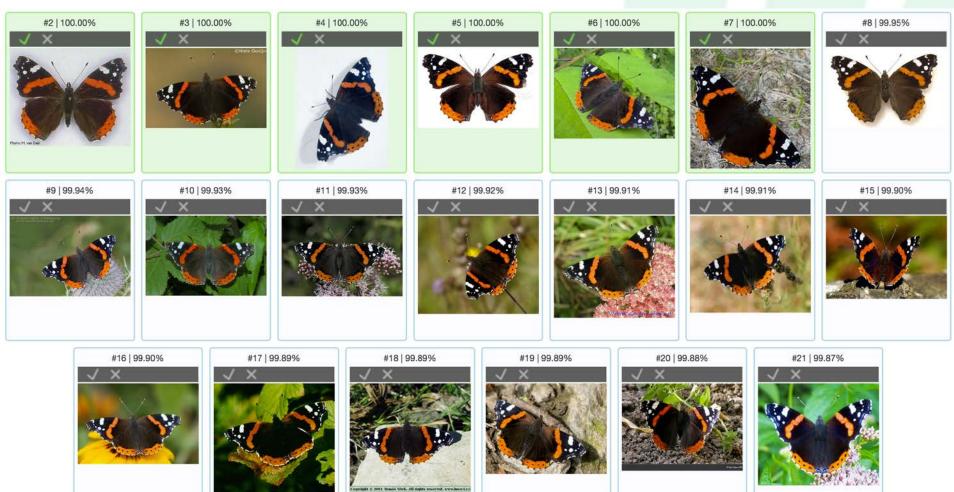


Interactive Query Refinement



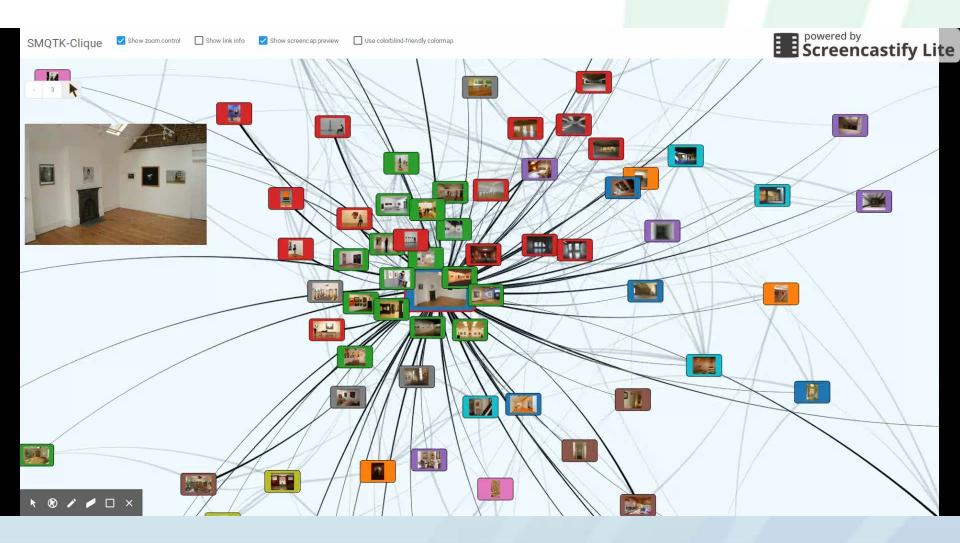


One Refinement Based on Adjudications from





Visualization of Image-Induced Networks





Social Multimedia Query ToolKit (SMQTK)

- Indexing, Searching and Query Refinement on any images
- Rapid query times from ITQ-based indexing
- Plugin based architecture allows rapid prototyping and experimentation
- Open source at KWIVER.org
- Web Based Sample Apps





FMV vs. AlexNet data

ImageNet "automobile"







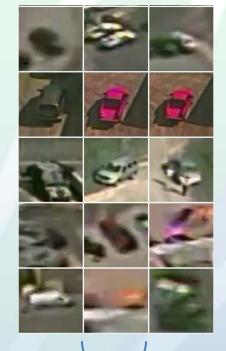






AlexNet: 224x224 chips

A.P. Hill "vehicle"

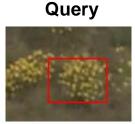


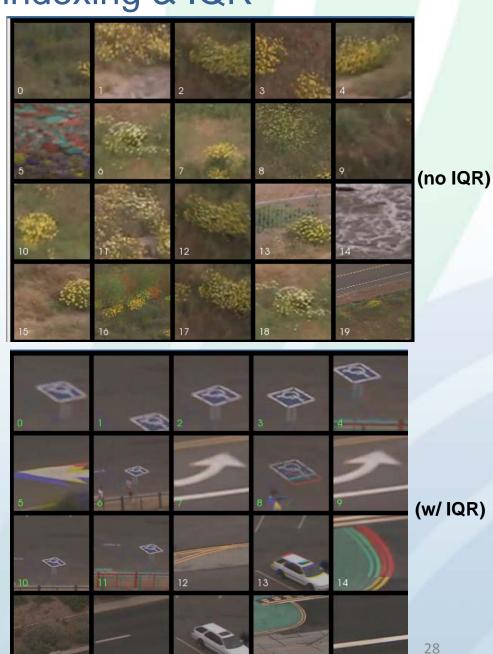
FMVNet: 96x96 chips



Neovision data w/ VIRAT indexing & IQR

Neovision data ingested into VIRAT framework, using FMVNet FC7 descriptors and motion & saliency detectors.





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Query



Data: Neovision CNN: FMVNet Detector: Motion & Saliency Descriptors: CNN FC7 Indexing: VIRAT



Neovision in SMQTK

Results after a few rounds of IQR and a re-query of the database







Data: Neovision CNN: AlexNet Detector: Windowing Descriptors: AlexNet Indexing: SMQTK

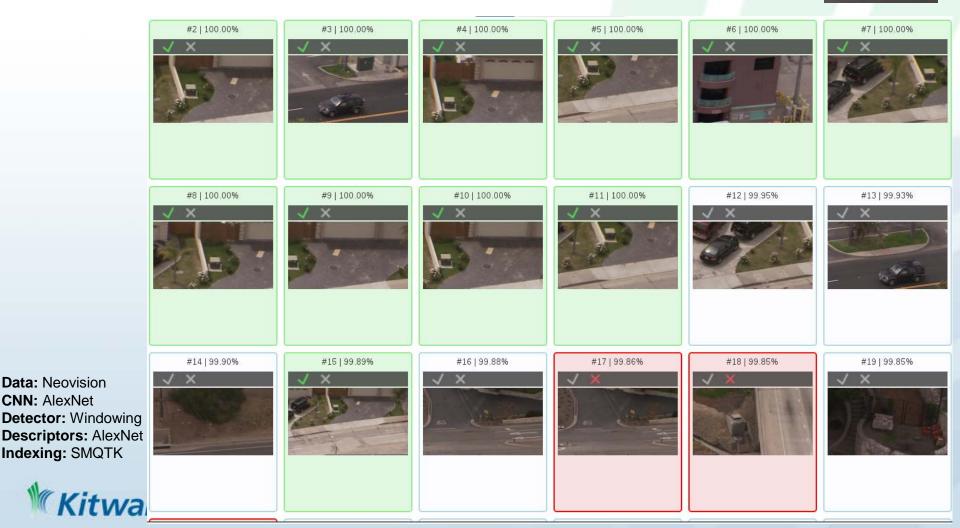


Neovision in SMQTK

Data: Neovision **CNN:** AlexNet

- Results obtained with IQR but no re-querying of the database. - Several rounds were required to train the model away from cars and windows.





KWIVER.org

Kitware Image and Video Exploitation and Retrieval Toolkit

An Open Source, production-quality video analytics toolkit

Streaming FMV

Social Multimedia Query ToolKit



VIBRANT: Video and Image-Based Retrieval and Analysis Toolkit Archive Query

Motion-imagery Aerial Photogrammetry Toolki





Summary

- Dramatic, disruptive advances in deep learning for computer vision are fueled by:
 - Big Data
 - GPU computation
 - Open source software
- Various tricks can greatly reduce training data requirements
- The ISR community should rapidly adopt deep learning for sensor exploitation problems
- To learn more, come to Honolulu on July 21-26 for the IEEE/CVF Conference on Computer Vision and Pattern Recognition



