

Fuzzing, Feature Deprecation, Causal Models and Metaphors:

How to make AI more Robust from experience on the Vision/Robotics Front.

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OpenCV.org

Opensource Computer Vision Library Foundation

Mission: Accelerate the Beneficial Uses of Computer Vision in Society



Background Pertinent to this Talk

- Founded the most popular **Opensource Computer Vision** library **OpenCV**
- Founded, run, involved with many computer vision and robotics startups
 - **SOLD:** Video Surf (*Video Search – Sold to Microsoft*), Industrial Perception (*Robotics in Logistics – Sold to Google*), Arraiy (*Camera Tracking in Broadcast and Movies – Sold to MatterPort*);
 - **ONGOING:** Gauss Surgical (*Surgery Monitoring*), OpenCV.ai (*Computer Vision Contracting*), Farm-ng (*Robotic Tractor, Visual Navigation*)
- Led Vision Team on Stanley, Winner of the DARPA Grand Challenge
 - Now in the Smithsonian – it kickstarted the Autonomous Driving Industry



What is OpenCV?

Open, Free for Commercial or Research Use, Computer Vision and AI Library

OPENCV LIBRARY

Soureforge Downloads:

22,757,138

Github:

~14,980 Unique Clones/Week

~63,560 Unique Visitors/Week

OpenCV.org:

- Maintains the code
- Produces courseware
- Partners to produce hardware
- Sponsors contests
- Runs workshops
- Sponsors Interns

54K

54K STARS ON GITHUB

github.com/opencv/opencv

61.4K stars: opencv + opencv_contrib

Extremely popular Github repo

1-2M

INSTALLS PER WEEK

[pypistats.org/packages/opencv-python](https://pypi.org/packages/opencv-python)

Rivals Tensorflow in Python
installs using pip

89%

EMBEDDED VISION ENGINEERS

embedded-vision.com/academy/ToolsAndProcessorsForCV_Jan2019_R1.pdf

The most popular Computer Vision
library among embedded vision engineers

2500

ALGORITHMS

github.com/opencv/opencv

The largest collection of Computer Vision
algorithms in a single library

OpenCV at a glance

HighGUI
I/O, Interface

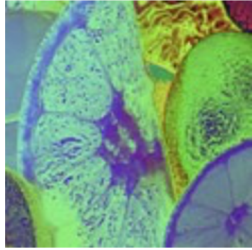


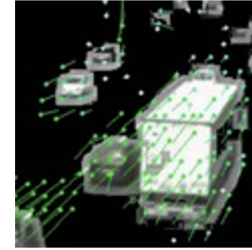
Image
Processing



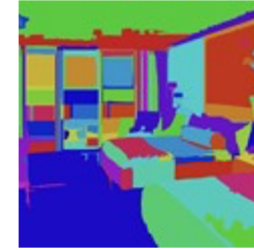
Transforms



Fitting



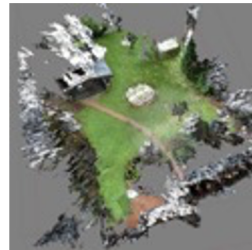
Optical Flow
Tracking



Segmentation



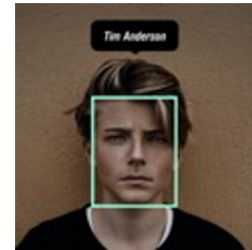
Calibration
Geometry
Color



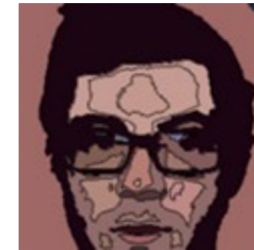
Features
VSLAM



RGBD
Depth, Pose,
Normals, Planes

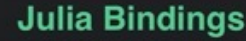


Deep Learning,
Machine Learning

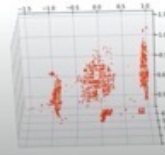


Computational
Photography

Core
Data structures, Matrix math, Exceptions etc




Compute L1 norm with

[illegible]

Tracking using SIAMRPN++

A white banner with the OpenCV logo at the top, followed by 'SHENZHEN UNIVERSITY' in red and black text, and 'china CHINA' at the bottom.



Large-scale Depth Fusion

OpenCV Web demos

Handbook of Mathematical Models in Computer Vision

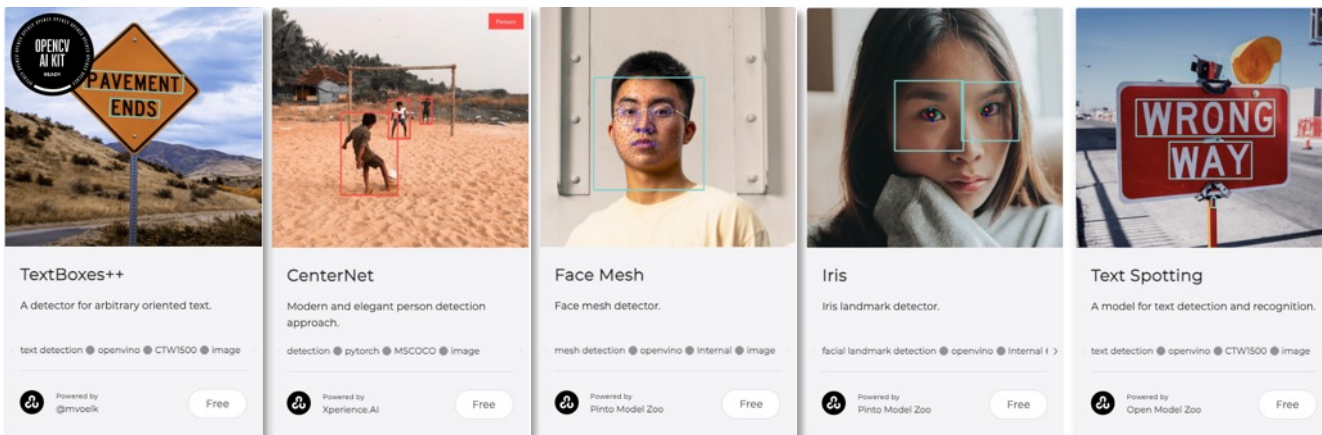
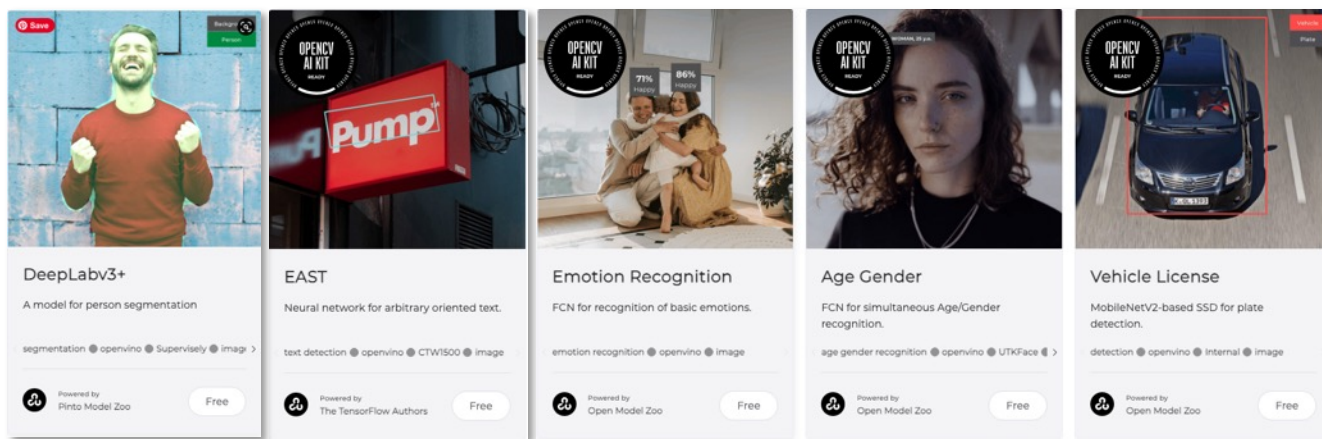
**Accurate Text
Detection &
Recognition**

Recent: Modelplace.AI

<https://modelplace.ai/>



- A model zoo for OpenCV, Community and Commercial models:
 - Optimized, trainable, tunable, memory efficient models
 - Drop image on browser to test:





Recent: HARDWARE -- OPENCV AI KIT (OAK)

OpenCV AI Kit with Depth (OAK-D) is
OpenCV's spatial AI camera based on Intel®
Myriad™ X.

4 Tera Ops/second

It can **run neural networks** for tasks like
image classification, object detection,
segmentation, pose estimation etc. in real
time.

It comes with a stereo pair for **depth
perception** in real time.

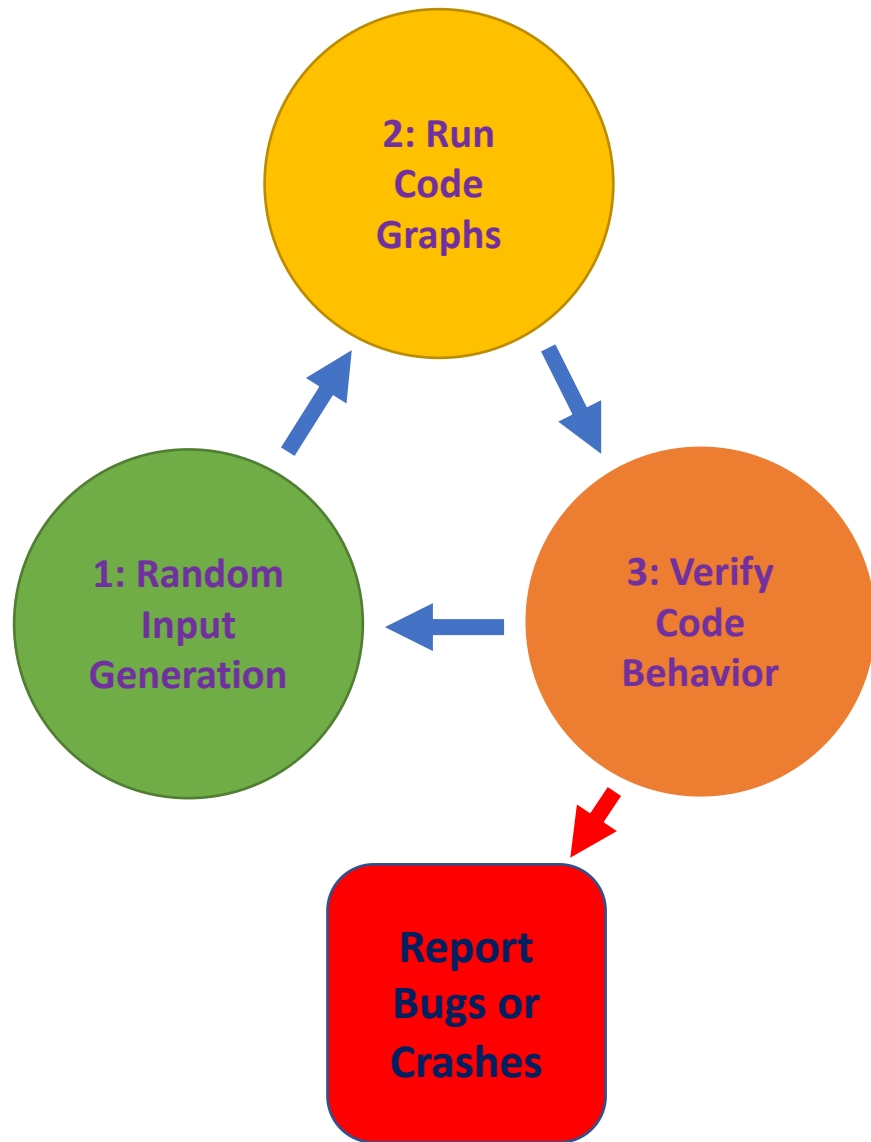




Problem #1:

Secure Code

Solution 1: Fuzzing



Deep Nets

- Need traditional Fuzzing
- And “Structural fuzzing”:
 - In vision, this might be random shapes, noise, lighting, glare, 3D perspective changes, object orientations etc
 - Check that it doesn’t destabilize results



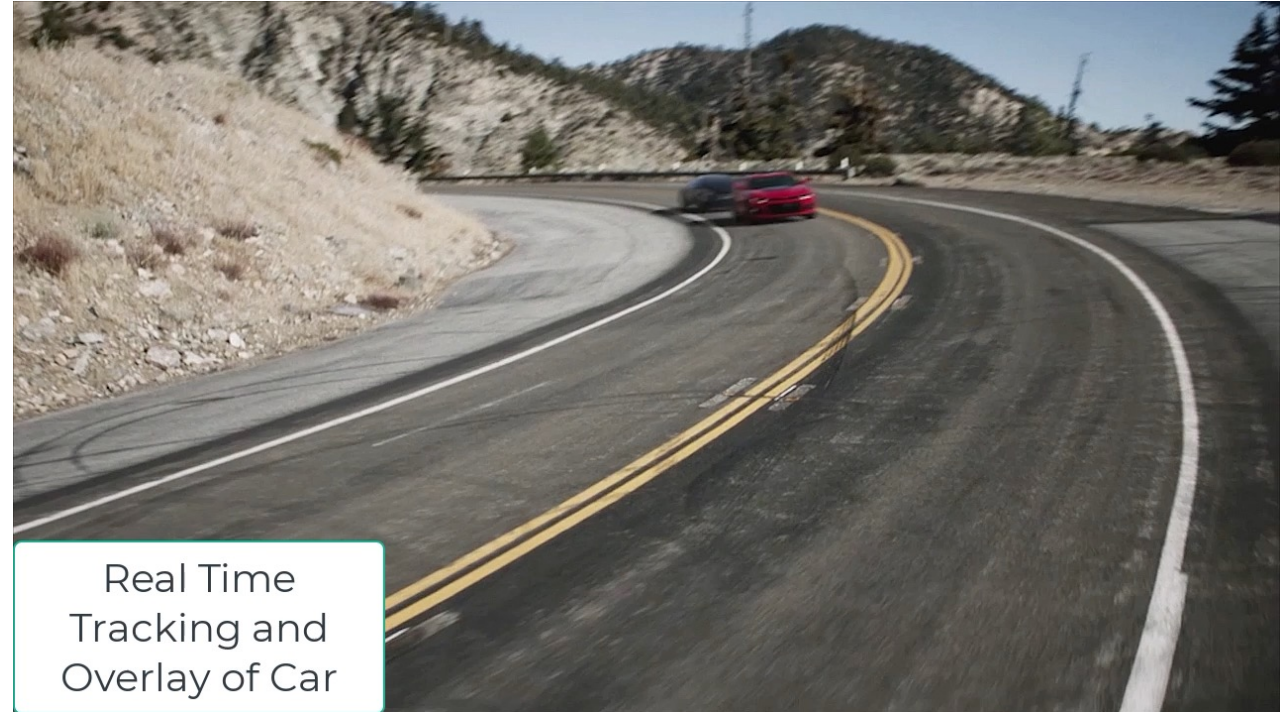
Company: Arraiy.com

Problem #2: Robustness in the field

- We must not fail at tracking camera location on set
- Regardless of objects or people in the way
- Lighting changes
- Changes to the set

Solution #2: Feature Deprecation

- Do not let the network get over reliant on any feature (here, geometric structures in the scene)
 - Randomly occlude parts of the scene during learning
 - If a feature starts growing strong, hide it (blur it out)
- We thus cause the network to rely on robust overall context in a scene



Farm-ng.com

These film techniques are now generalized (licensed) to:

- Robot navigation in agricultural fields and in logistics
- Solving GPS denial in Defense
 - Drones, Planes, Rovers, Boats
- NASA moon lander



**Farm-ng
Robot Tractor**





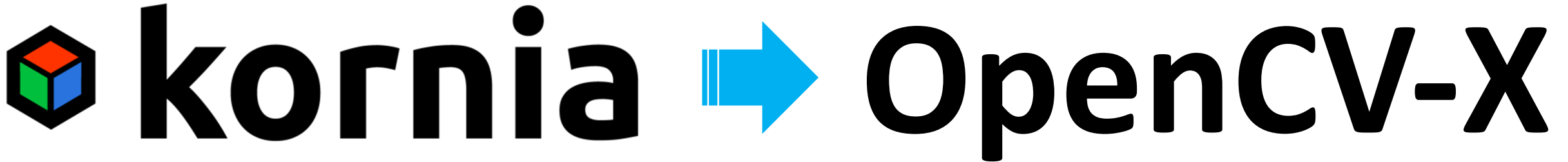
Gap #3:

How to use Programmatic Operators in Deep Nets



Solution #3: (for Vision)

Use PyTorch to create differentiable vision operators that can work w/in and around networks



Open Source Differentiable Computer Vision Library for  PyTorch

Edgar Riba; Dmytro Mishkin; Daniel Ponsa; Ethan Rublee; Gary Bradski, “Kornia: an Open Source Differentiable Computer Vision Library for PyTorch”, WACV 2020

E. Riba, D. Mishkin, J. Shi, D. Ponsa, F. Moreno-Noguer and G. Bradski, “A survey on Kornia: an Open Source Differentiable Computer Vision Library for PyTorch”, <https://arxiv.org/abs/2009.10521>, 2020

E. Riba, M. Fathollahi, W. Chaney, E. Rublee and G. Bradski, “Torchgeometry: when PyTorch meets geometry”, PyTorch Developer Conference, 2018, https://drive.google.com/file/d/1xiao1Xj9WzjJ08YY_nYwsthE-wxfyhG/view?usp=sharing



OpenCV-X

core features



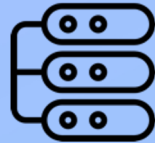
Computer Vision



Differentiable



Transparent API



Parallel Programming



Distributed



Production



Problem #4:

Common sense and Reasoning

Solution #4:

Causal Models and Metaphors

The DARPA Grand Challenge

- \$2M robot car race across the desert
- Kicked off the autonomous driving industry
- Stanford's Stanley won
- Now in the Smithsonian



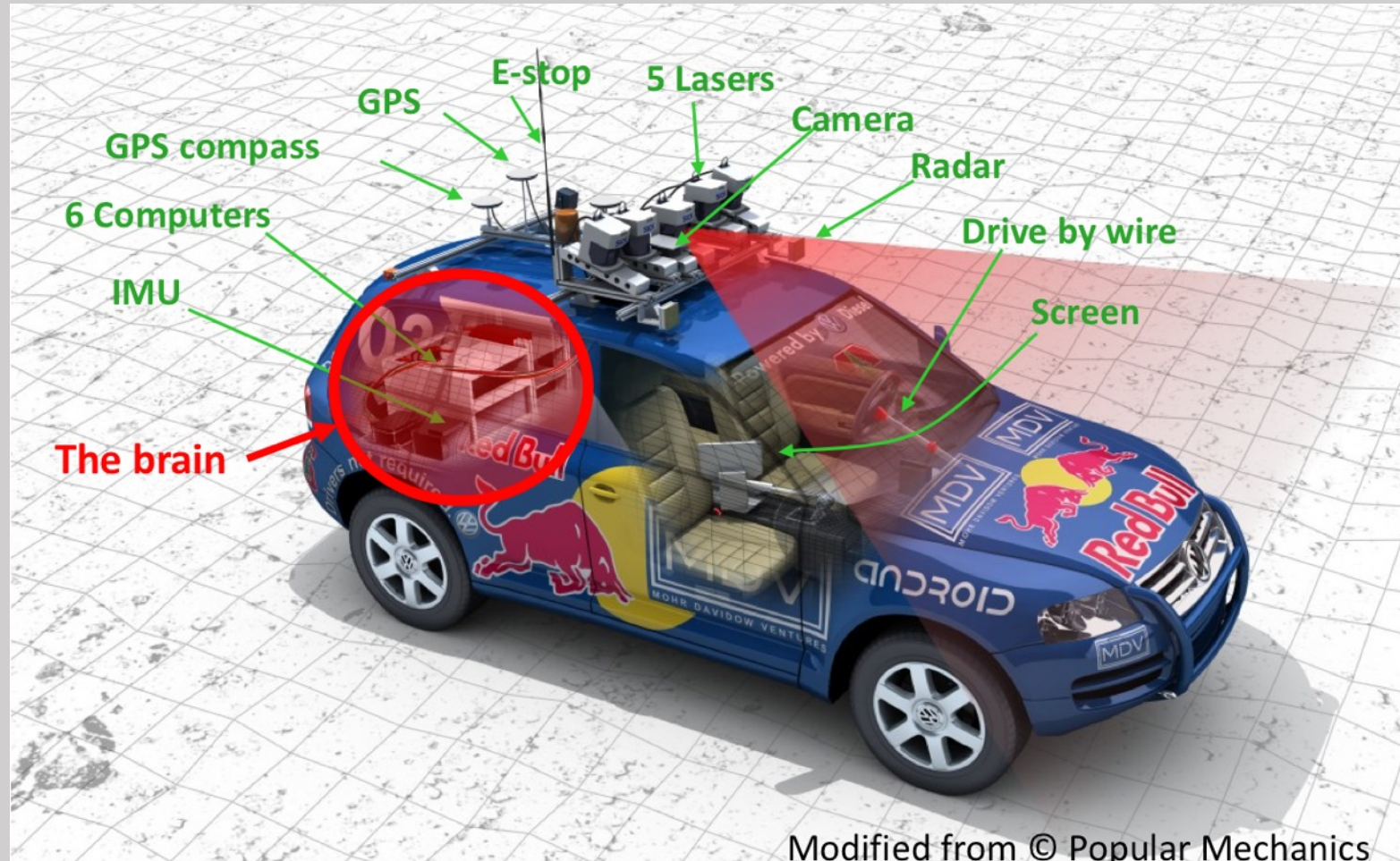
DARPA Grand Challenge



The DARPA Grand Challenge is a prize competition for American autonomous vehicles, funded by the Defense Advanced Research Projects Agency, the most prominent research organization of the United States Department of Defense. [Wikipedia](#)

© Popular Mechanics

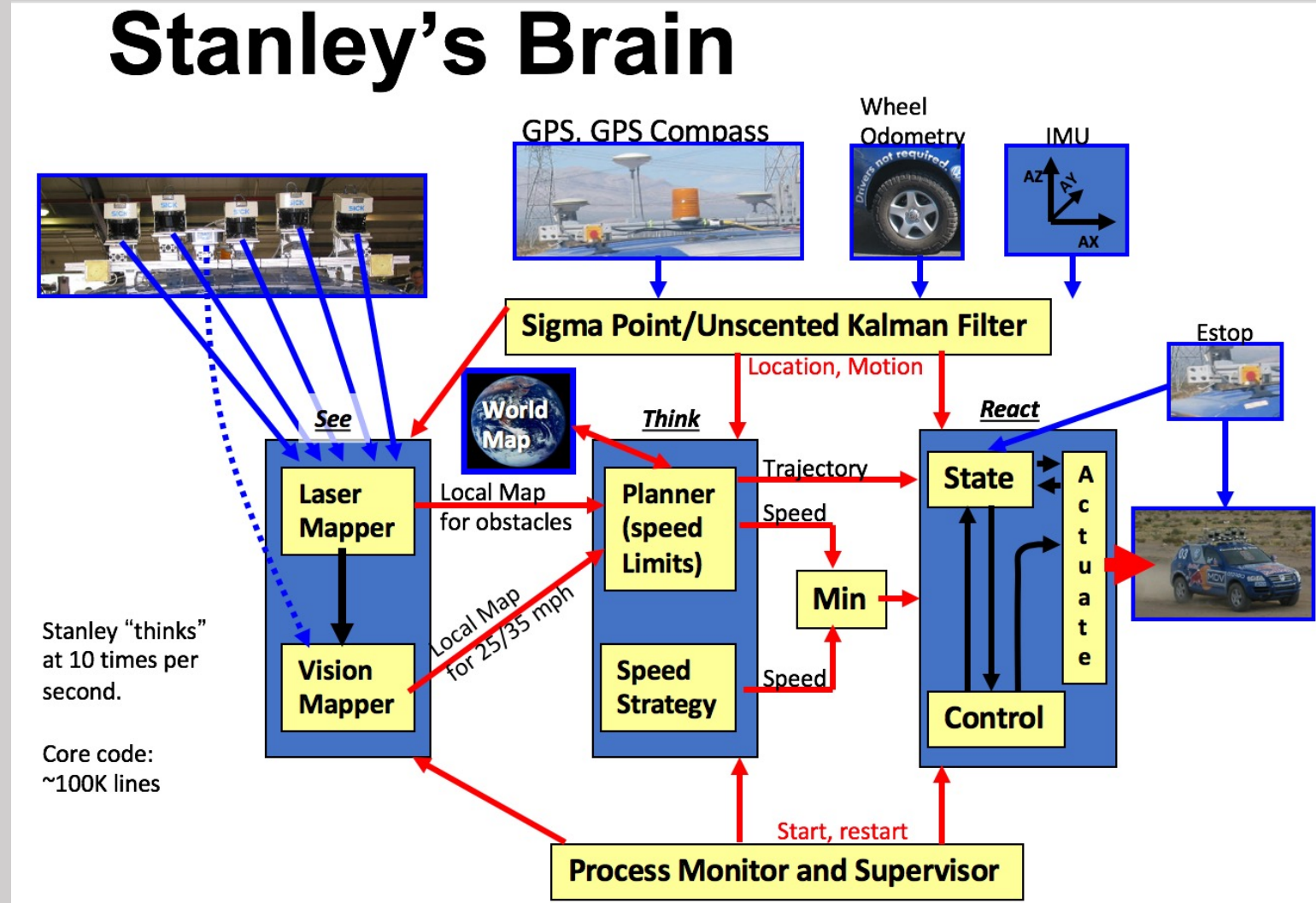
Stanley's Sensing



Picture 2

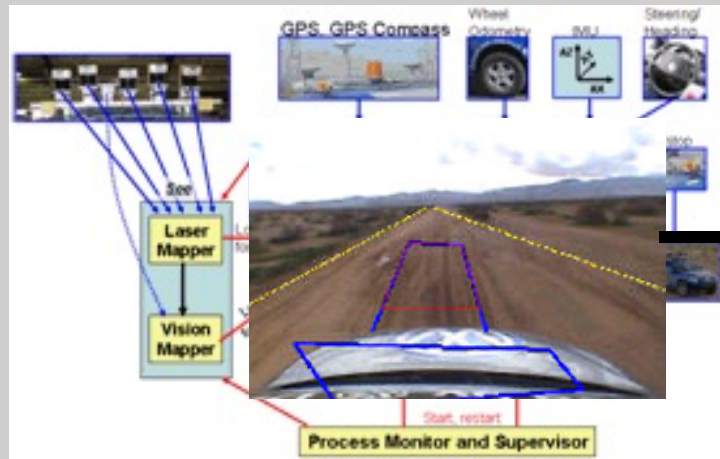
Stanley's Brain

- Many sensors being fused in a planning map
- Sensing is reformatted for the mind



Stanley's "Mind"

Sensors are fused into a map: Seeing => Perception

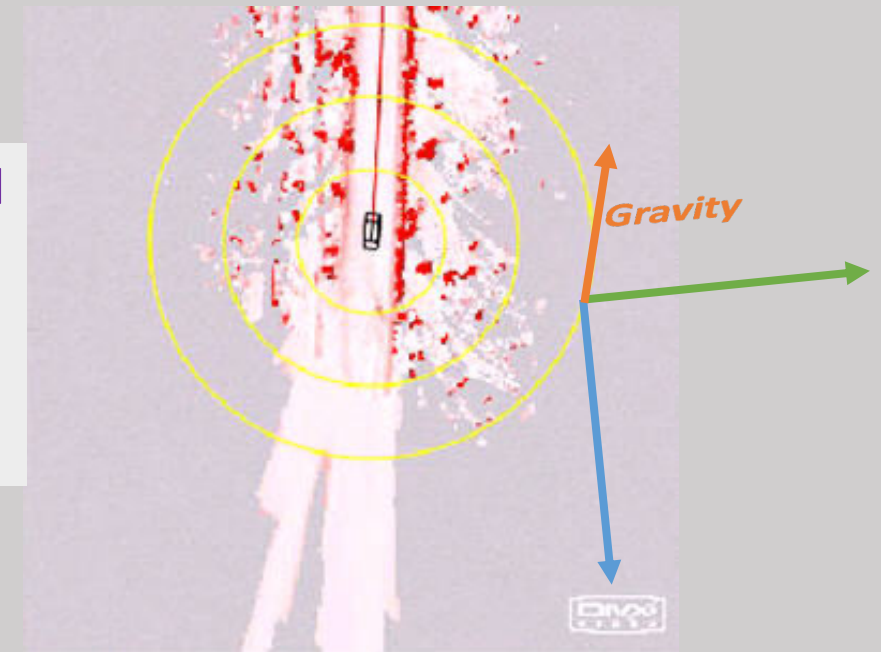


Fused into bird's eye world model



The map has only: **red => bad**; **gray => don't know**; **white => drivable**.
The map also has **tilt** and **direction of gravity**.

Bird's eye world model
+
Gravity direction
+
Physics



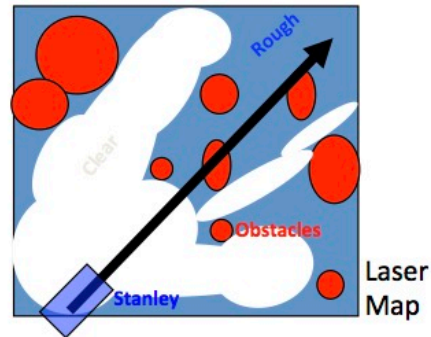


Stanley's Mind

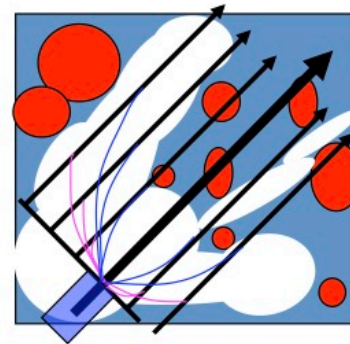
Recognition + Simulation/Plan => Action

From the map and its tilt, the robot and it's driving plans/goals are (physics) simulated. THIS SIMULATOR IS A CAUSAL MODEL that is matched against the world

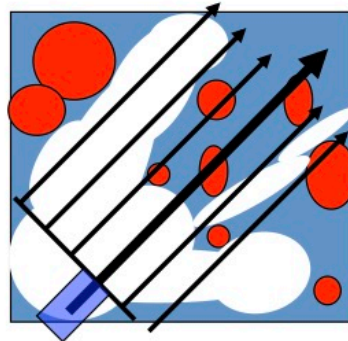
1) Base Trajectory:



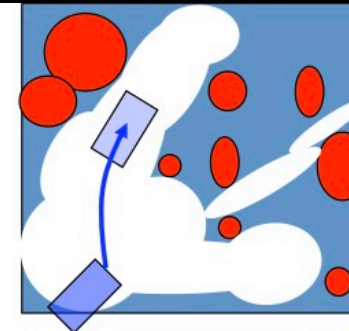
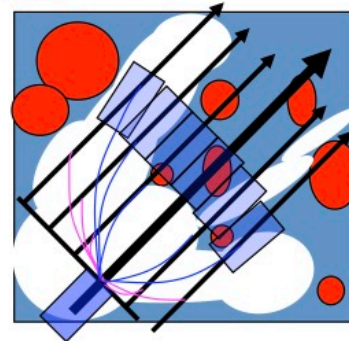
3) "Nudges" and "swerves":



2) Parallel offsets:



4) Controller "drives" the paths:



The paths are generated obeying kinematic and dynamic constraints. They can be driven.

Best action chosen subject to external and learned rules

And a final decision is made.



Solution #4: Matching Learned Models

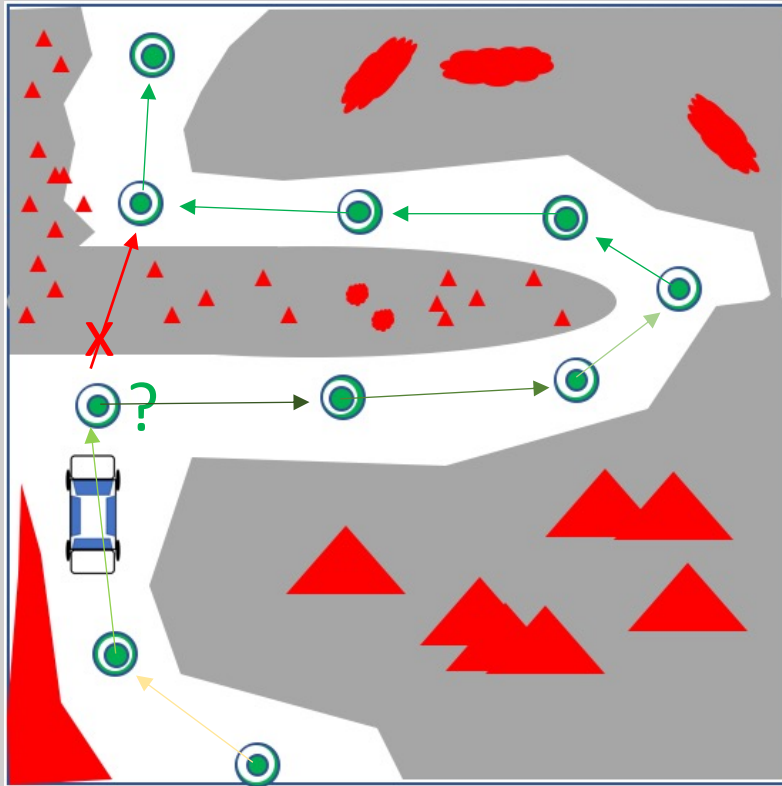
Key takeaways for why our perception is more robust than deep nets:

- **Deep Nets use**
 - matching (against loss functions) to learn
 - Inference to predict
- **Robots/Humans use**
 - Correlation to learn
 - Matching against a causal model to recognize

Note on: Stanley's Programming:

- Emotions program “WHAT to do”
- Mind finds “HOW to do it”

Stanley “wanted” to follow GPS way points quickly and in sequential order



The “Mind” is “How”
The “Emotions” are “What”

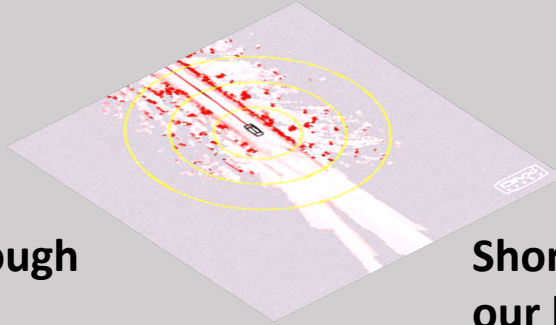
Generalizing Learning:

Reason with the metaphors you've got

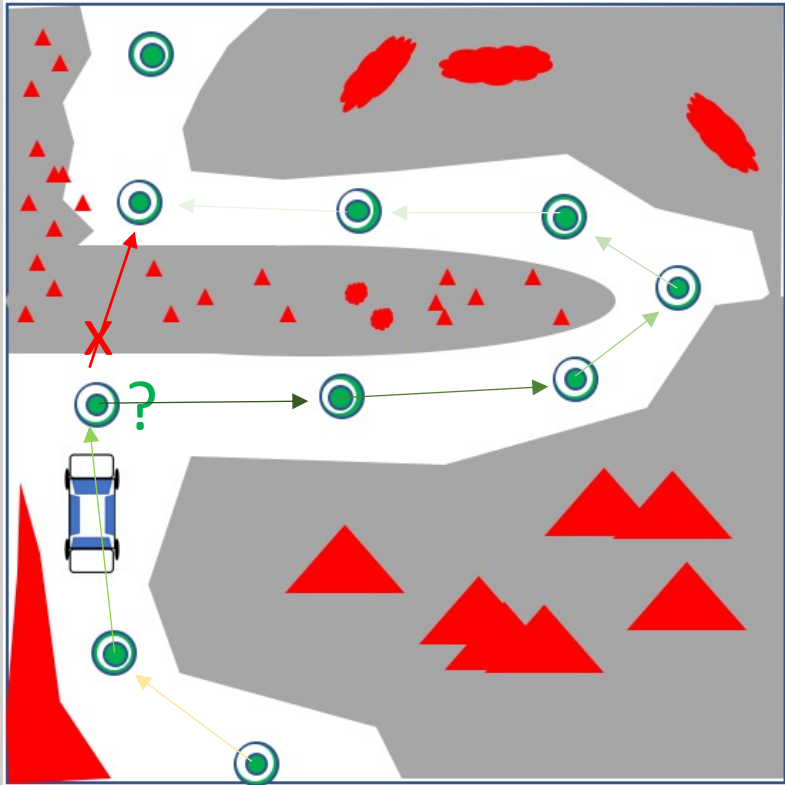
- **Explain Shakespeare to a cat:**
- Even if your cat had listened to Shakespeare since it was a kitten.
 - Would you expect it to understand Shakespeare?
 - Perhaps a morality tale of a kitten that is tragically too bold?



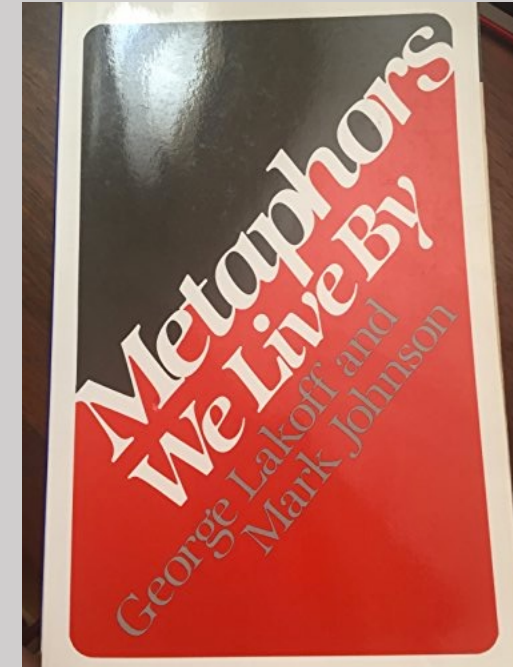
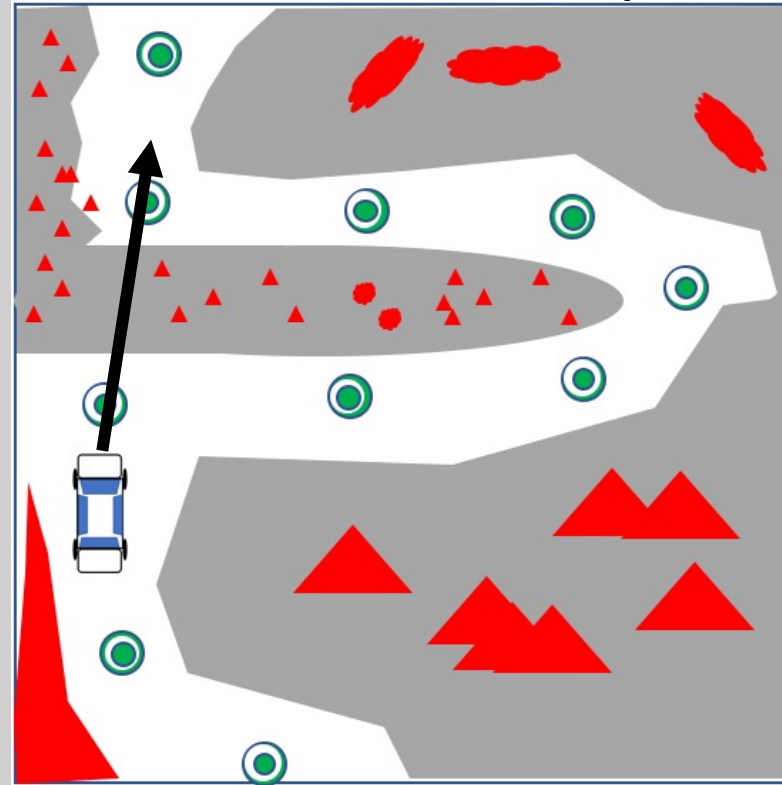
Metaphors: Communicating Shakespeare's Hamlet plot to the robot Stanley



The “hero” needs get through waypoints fast:



Shortsightedness in thinking causes our hero to take a destructive path:



Takeaways (Solution #4, extending learning via reasoning):

- (1) Reasoning can extend the mind far beyond just raw “training”
- (2) Reason breaks down when the causal primitives aren’t rich enough



Key Points about a robust mind:

STABILIZED PERCEPTION/PLANNING

- Some causal model priors are tuned into a causal model of the world
- Matching this model against world data provides robust perception
- The causal model is used in simulations of mind's world representation in order to plan
 - The causal grounding of the mind's model in the external world stabilizes perception
 - The simulation is not a "*true representation*", but it is **causally** accurate for that mind

GENERALIZING LEARNING

- The models that the mind learns may be used to generalize learning via metaphor
- This allows “transfer learning reasoning”
- The brain is ultimately limited by the richness of its causal models





FINISH

QUESTIONS?



Photo: Gary Bradski