Image-Based Situation Awareness Audit 28.2.2018

Sakari Lampola

Previous Audit 11.1.2018

Previous Audit

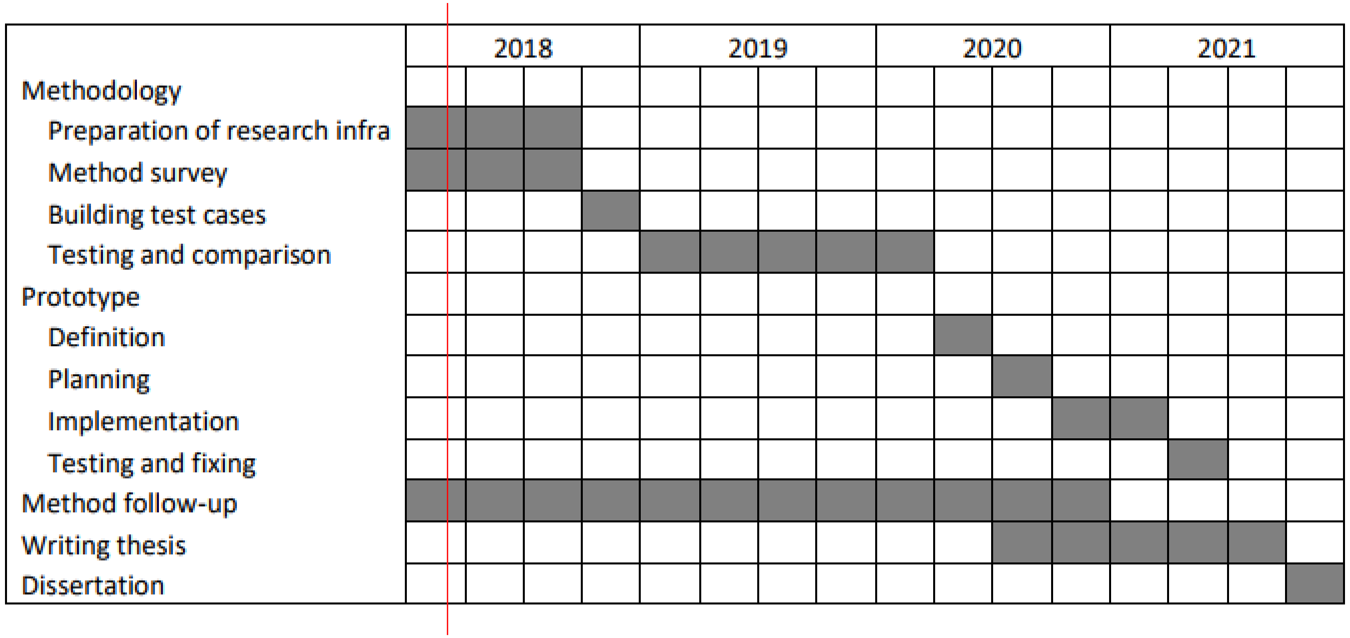
Open questions:
- Role of classical object tracking alrorithms?
- What to do with multiple bounding boxes around one object?
- Appropriate minimum confidence level?
- What to do with false detections inside other objects?
- What to do with false detections from the background?
- How to set Kalman filter parameters for image object filtering?
- Hungarian algorithm, special case for hidden objects

To do:
- Close open questions
- Image object status
- Image object velocity estimation
- Probabilistic approach for matching detected and image objects
- 2d -> 3d transformation
- World object state estimation

Other:
- Semantic segmentation
- Organisations to follow: ICCV, ICRA, NIPS, IROS, arXiv
- Camera motion (yaw, pitch,roll)
- Grid or continuos presentation?
- Class specific attributes
- Object history

Project Plan

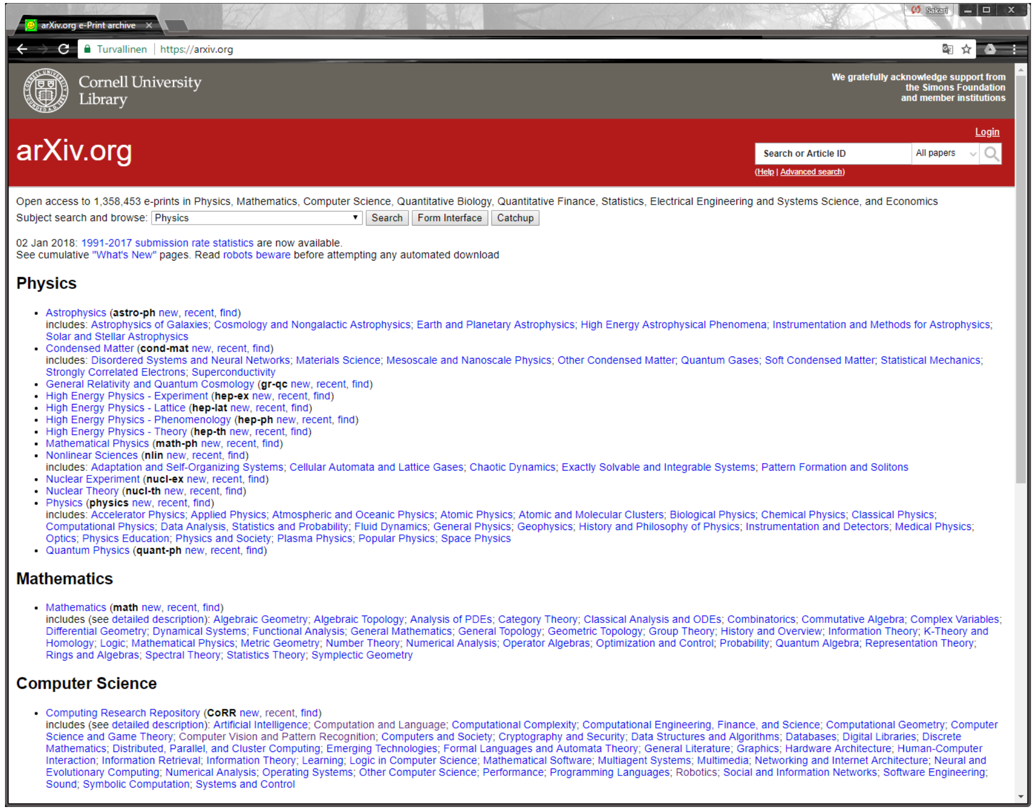
Project Plan

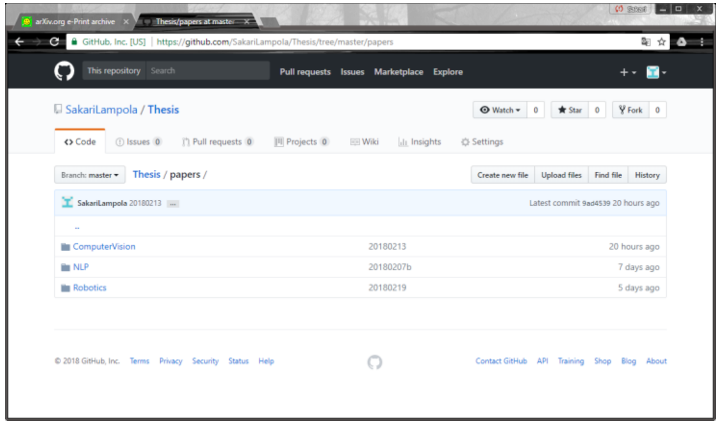


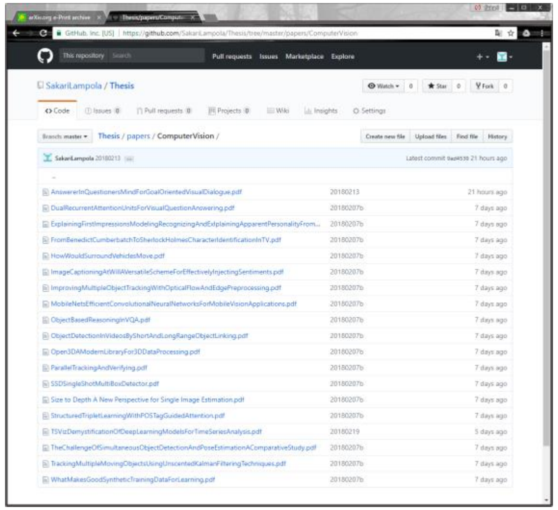
1. Methodology / Preparation of research infra
   a. Software platforms are constructed and tested
   b. Off-the-shelf models are acquired and tested
   c. Necessary skills on platforms are learned
2. Methodology / Method survey
   a. Current state-of-art methods are studied
   b. Methods are constructed and tested on the software platforms
3. Method follow-up
   a. Screening of conference papers related to the subject
   b. Possibly integrating new methods to the project

Work Done

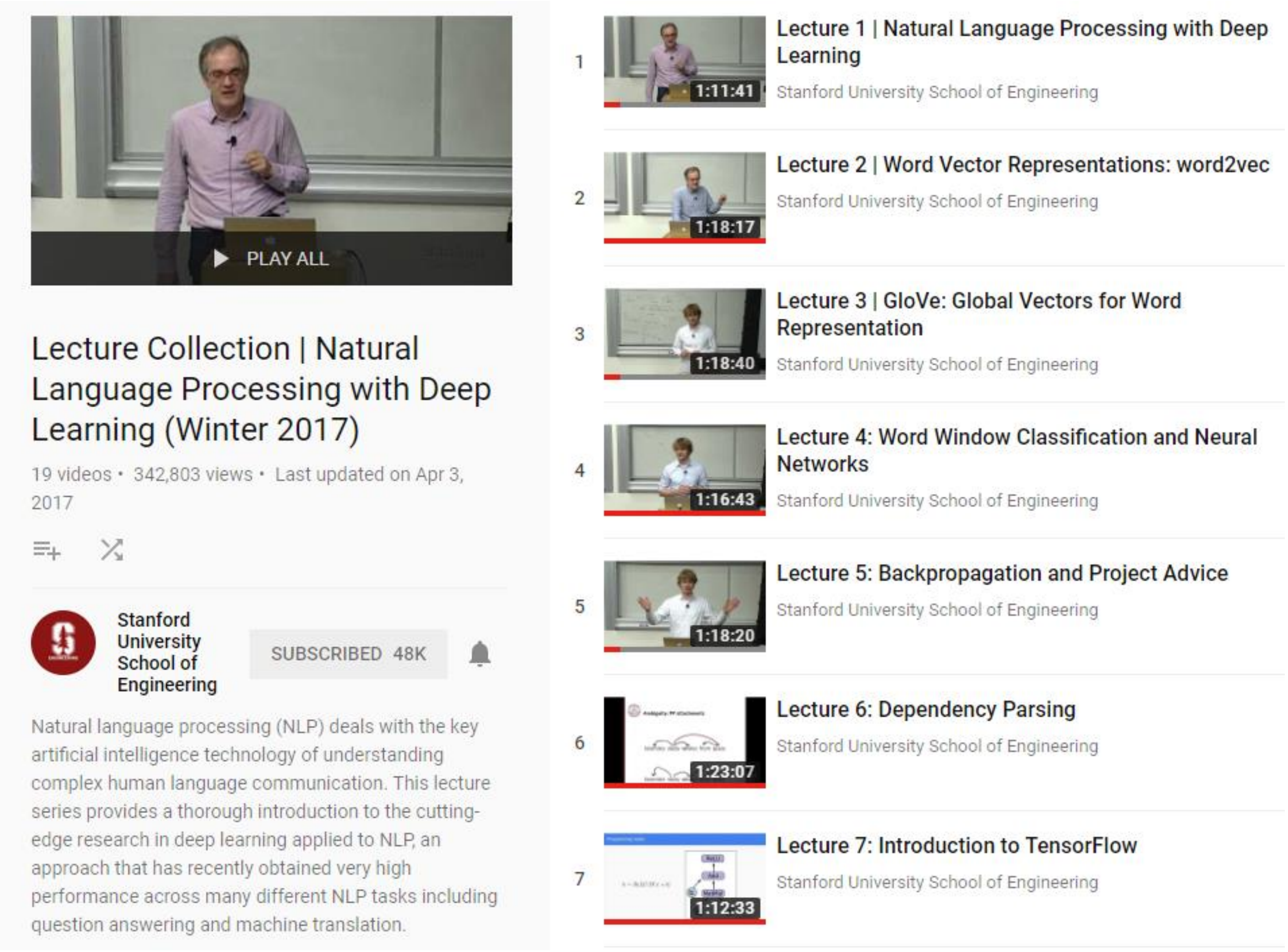
Method Follow-Up







Method Survey



Christoffer Manning & Richard Socher

Method Survey

8 Lecture 8: Recurrent Neural Networks and Language Models — 1:18:03
Stanford University School of Engineering

9 Lecture 9: Machine Translation and Advanced Recurrent LSTMs and GRUs — 1:20:28
Stanford University School of Engineering

10 Review Session: Midterm Review — 1:25:02
Stanford University School of Engineering

11 Lecture 10: Neural Machine Translation and Models with Attention — 1:21:24
Stanford University School of Engineering

12 Lecture 11: Gated Recurrent Units and Further Topics in NMT — 1:20:00
Stanford University School of Engineering

13 Lecture 12: End-to-End Models for Speech Processing — 1:16:35
Stanford University School of Engineering

14 Lecture 13: Convolutional Neural Networks — 1:22:12
Stanford University School of Engineering

15 Lecture 14: Tree Recursive Neural Networks and Constituency Parsing — 1:22:08
Stanford University School of Engineering

16 Lecture 15: Coreference Resolution — 1:20:46
Stanford University School of Engineering

17 Lecture 16: Dynamic Neural Networks for Question Answering — 1:18:15
Stanford University School of Engineering

18 Lecture 17: Issues in NLP and Possible Architectures for NLP — 1:18:58
Stanford University School of Engineering

19 Lecture 18: Tackling the Limits of Deep Learning for NLP — 1:20:42
Stanford University School of Engineering

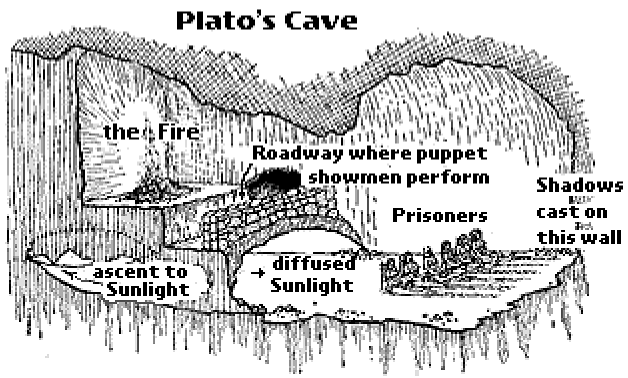
Goodfellow, Bengio, Courville: Deep Learning

Software Version 2.0

V2.0 Goal

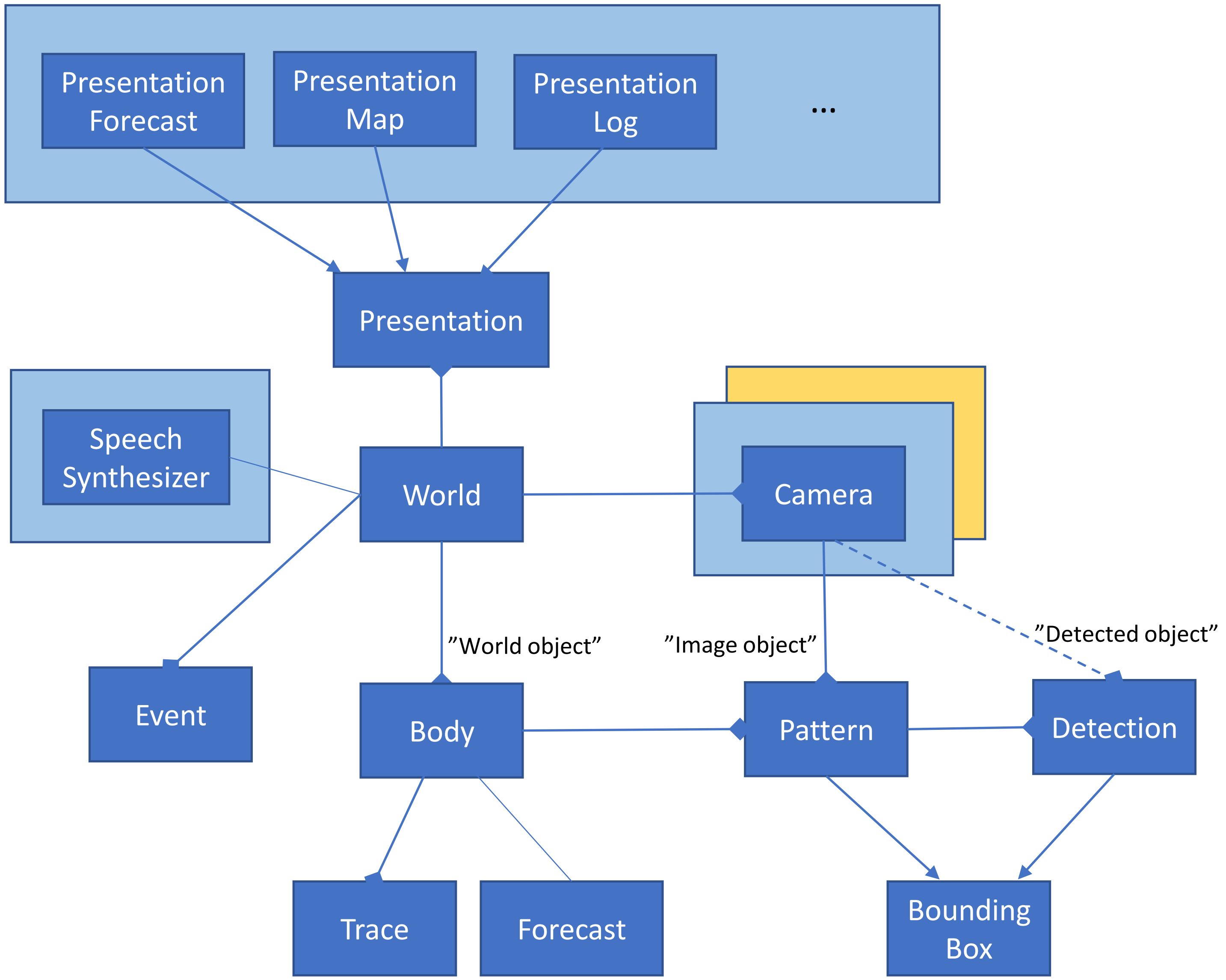
- Detected classes not hardcoded
- Object class may change
- Support for many cameras , rotations, movement
- Names less awkward, terminology fixed
- Cleaning
- Python style guide followed, excluding line length
- Code optimization
- One package
- Language (speech synthesizer)

Name of the software package: ShadowWorld
(Plato: Allegory of the Cave)



Software Version 2.0

Class Diagram



Software Version 2.0

Detection

Matching

Pattern Filtering

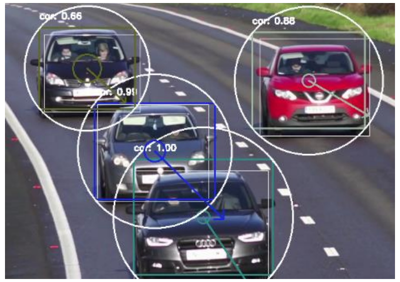
Distance Estimation

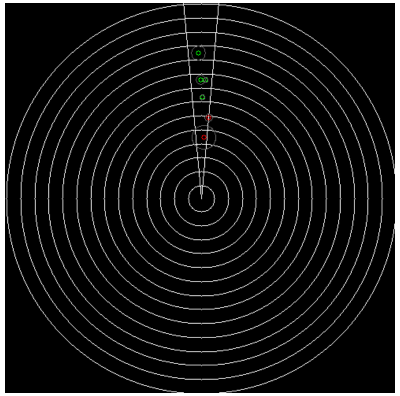
3D Projection

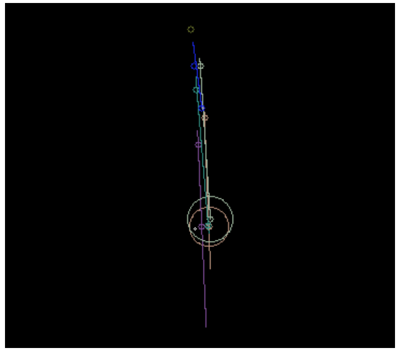
Body Filtering

Body Prediction

Collision Detection

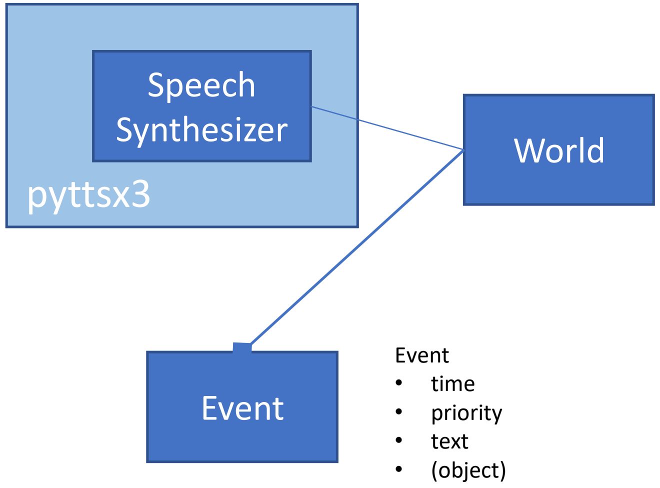






Software Version 2.0

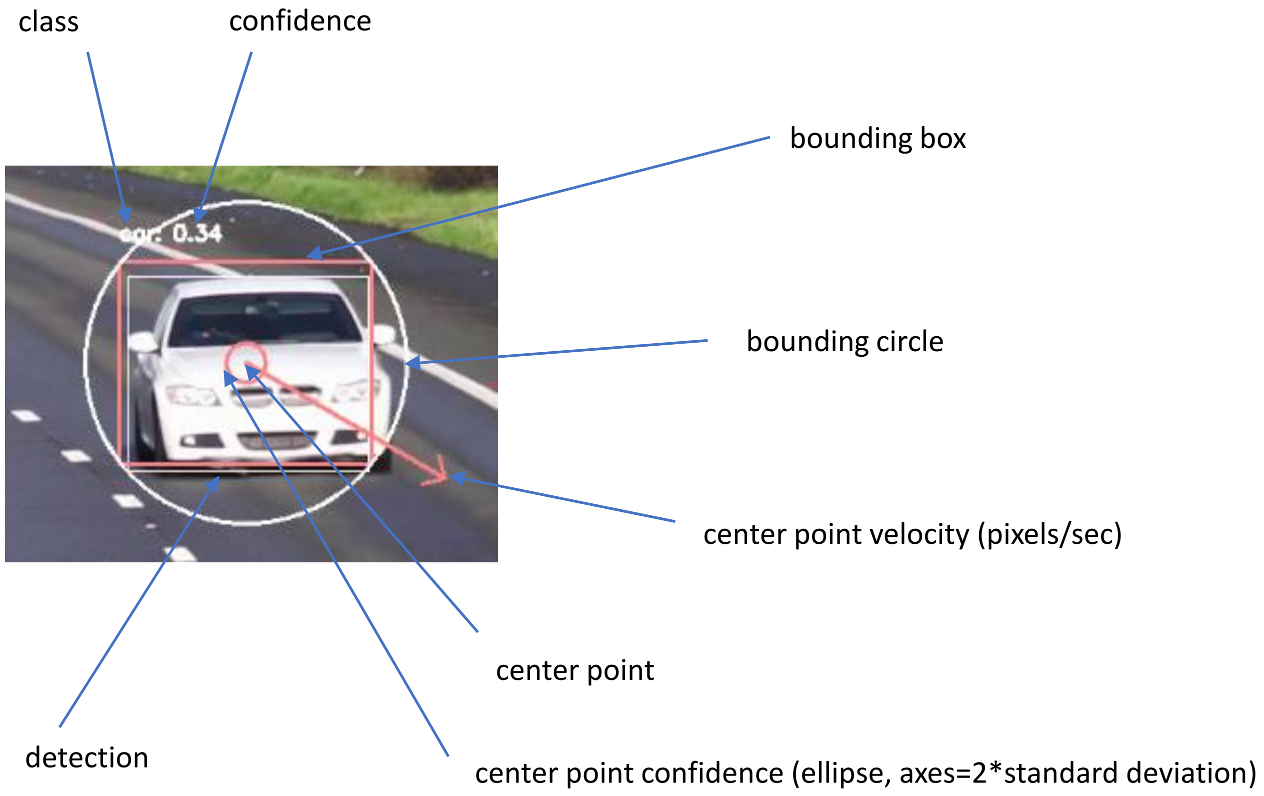
Language



- Speech synthesizer based on pyttsx3 package
- Event is spelled out if priority <= 0
- Event will pause video for the duration of speech (to be changed later by using separate thread)
- Example events:
  - Body observed (1 sec after created)
  - Collision warning
- Speech recognition later

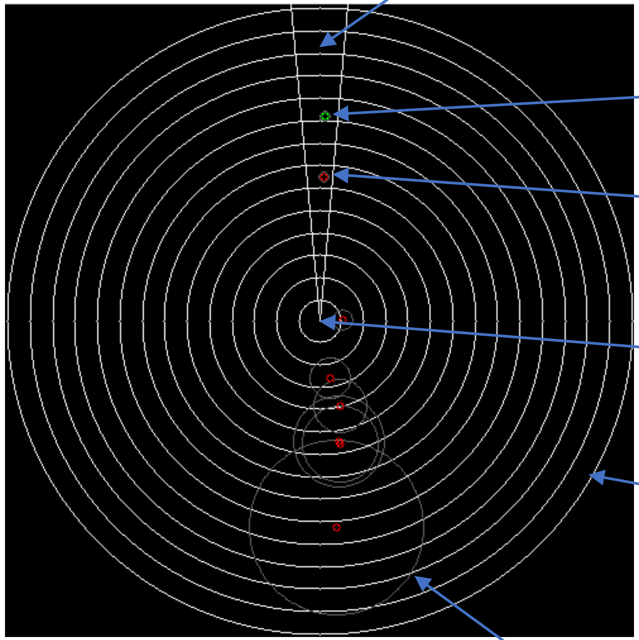
Software Version 2.0

Visual Presentation (pattern)



Software Version 2.0

Visual Presentation (body)



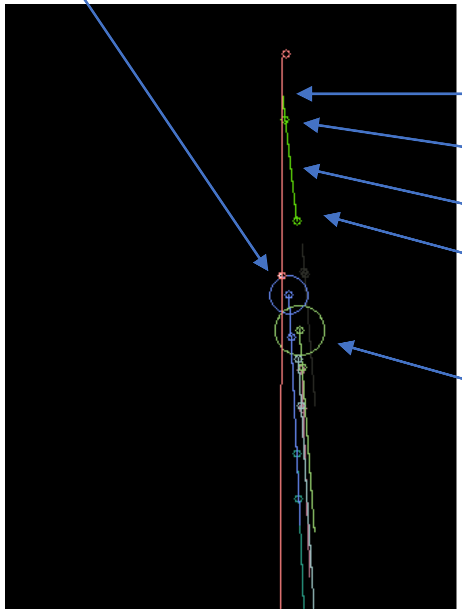
body size (circle, radius = mean class specific radius)

Software Version 2.0

Visual Presentation (forecast)

Forecast made every FORECAST_INTERVAL (=1.0) seconds

observer



body location, when forecast was made

body location, current

body location predicted path

body location after FORECAST_COUNT*FORECAST_DELTA seconds

collision probability > 1

body size (circle, radius = mean class specific radius)

Software Version 2.0

Logging

Body.txt | Detection.txt | Event.txt | Pattern.txt

```
time,id,class_id,x,y,z,vx,vy,vz,sigma_00,sigma_01,sigma_02,sigma_03,sigma_04,sigma_05,sigma_10
0.000,2061579034864,7,3.452,-0.145,-96.541,0.000,0.000,0.000,199.601,0.000,0.000,7.971,0.000,0
0.000,2061579035088,7,-0.226,-1.349,-89.454,0.000,0.000,0.000,199.601,0.000,0.000,7.971,0.000,
0.040,2061579034864,7,3.507,-0.183,-96.872,0.612,-0.426,-3.685,128.569,0.000,0.000,1429.181,0.
0.040,2061579035088,7,-0.209,-1.372,-88.698,0.182,-0.255,8.404,128.569,0.000,0.000,1429.181,0.
0.080,2061579034864,7,3.579,-0.228,-97.404,1.181,-0.758,-8.294,128.173,0.000,0.000,1536.731,0.
0.080,2061579035088,7,-0.193,-1.397,-88.220,0.289,-0.429,10.111,128.173,0.000,0.000,1536.731,0
0.080,2061579036712,7,0.591,2.067,-118.685,0.000,0.000,0.000,199.601,0.000,0.000,7.971,0.000,0
0.120,2061579034864,7,3.636,-0.299,-97.312,1.271,-1.158,-4.132,121.951,0.000,0.000,1198.603,0.
0.120,2061579035088,7,-0.170,-1.424,-87.496,0.405,-0.530,13.249,121.951,0.000,0.000,1198.603,0
0.120,2061579036712,7,0.620,2.098,-121.664,0.325,0.348,-33.111,128.569,0.000,0.000,1429.181,0.
0.160,2061579034864,7,3.706,-0.386,-97.300,1.425,-1.481,-2.710,111.067,0.000,0.000,888.002,0.0
0.160,2061579035088,7,-0.137,-1.478,-87.432,0.535,-0.791,9.528,111.067,0.000,0.000,888.002,0.0
0.160,2061579036712,7,0.650,2.122,-123.217,0.530,0.466,-35.849,128.173,0.000,0.000,1536.731,0.
0.160,2061579038560,7,-1.793,0.215,-107.421,0.000,0.000,0.000,199.601,0.000,0.000,7.971,0.000,
0.200,2061579034864,7,3.791,-0.455,-97.492,1.616,-1.550,-3.271,99.964,0.000,0.000,666.108,0.00
0.200,2061579035088,7,-0.103,-1.548,-87.545,0.624,-1.047,6.234,99.964,0.000,0.000,666.108,0.00
0.200,2061579036712,7,0.678,2.116,-122.864,0.597,0.220,-18.293,121.951,0.000,0.000,1198.603,0.
0.200,2061579038560,7,-1.802,0.192,-107.854,-0.108,-0.258,-4.809,128.569,0.000,0.000,1429.181,
0.240,2061579034864,7,3.848,-0.515,-97.046,1.572,-1.538,0.010,90.081,0.000,0.000,512.455,0.000
0.240,2061579035088,7,-0.066,-1.624,-87.436,0.688,-1.241,5.433,90.081,0.000,0.000,512.455,0.00
0.240,2061579036712,7,0.716,2.084,-121.887,0.710,-0.101,-4.624,111.067,0.000,0.000,888.002,0.0
0.240,2061579038560,7,-1.797,0.181,-107.885,0.003,-0.262,-2.878,128.173,0.000,0.000,1536.731,0
0.280,2061579034864,7,3.904,-0.567,-96.519,1.537,-1.489,2.623,81.625,0.000,0.000,404.376,0.000
0.280,2061579035088,7,-0.025,-1.708,-87.195,0.758,-1.408,5.551,81.625,0.000,0.000,404.376,0.00
0.280,2061579036712,7,0.769,2.066,-121.510,0.873,-0.200,-0.880,99.964,0.000,0.000,666.108,0.00
0.280,2061579038560,7,-1.769,0.157,-107.973,0.283,-0.392,-2.613,121.951,0.000,0.000,1198.603,0
0.320,2061579034864,7,3.953,-0.616,-95.888,1.480,-1.443,4.926,74.449,0.000,0.000,326.355,0.000
0.320,2061579035088,7,0.022,-1.804,-86.974,0.830,-1.582,5.549,74.449,0.000,0.000,326.355,0.000
0.320,2061579036712,7,0.817,2.006,-119.710,0.947,-0.494,9.559,90.081,0.000,0.000,512.455,0.000
0.320,2061579038560,7,-1.721,0.126,-107.255,0.571,-0.520,3.968,111.067,0.000,0.000,888.002,0.0
0.360,2061579034864,7,4.001,-0.664,-95.265,1.438,-1.405,6.601,68.343,0.000,0.000,268.528,0.000
0.360,2061579035088,7,0.071,-1.908,-86.738,0.890,-1.744,5.602,68.343,0.000,0.000,268.528,0.000
0.360,2061579036712,7,0.859,1.938,-117.821,0.968,-0.734,17.022,81.625,0.000,0.000,404.376,0.00
0.360,2061579038560,7,-1.646,0.099,-105.881,0.925,-0.559,12.064,99.964,0.000,0.000,666.108,0.0
0.400,2061579034864,7,4.041,-0.712,-94.469,1.374,-1.377,8.493,63.113,0.000,0.000,224.623,0.000
0.400,2061579035088,7,0.117,-1.992,-86.240,0.928,-1.796,6.576,63.113,0.000,0.000,224.623,0.000
0.400,2061579036712,7,0.904,1.869,-116.026,0.994,-0.907,21.908,74.449,0.000,0.000,326.355,0.00
0.400,2061579038560,7,-1.589,0.174,-104.160,1.036,-0.006,19.110,90.081,0.000,0.000,512.455,0.0
0.440,2061579034864,7,4.064,-0.759,-93.474,1.272,-1.349,10.624,58.597,0.000,0.000,190.567,0.00
0.440,2061579035088,7,0.164,-2.066,-85.548,0.961,-1.802,7.971,58.597,0.000,0.000,190.567,0.000
0.440,2061579036712,7,0.963,1.810,-114.711,1.072,-0.997,23.628,68.343,0.000,0.000,268.528,0.00
0.440,2061579038560,7,-1.524,0.192,-102.873,1.154,0.087,21.695,81.625,0.000,0.000,404.376,0.00
0.480,2061579034864,7,4.068,-0.806,-92.157,1.129,-1.329,13.295,54.666,0.000,0.000,163.653,0.00
0.480,2061579035088,7,0.214,-2.135,-84.872,0.995,-1.793,9.042,54.666,0.000,0.000,163.653,0.000
0.480,2061579036712,7,1.026,1.753,-113.527,1.142,-1.056,24.481,63.113,0.000,0.000,224.623,0.00
```

Software Version 2.0

How to use?

```
def run_application():
    """
    Example application
    """
    test_video = 5

    world = World()

    world.add_camera(Camera(world, focal_length=TEST_FOCAL_LENGTHS[test_video],
                            sensor_width=0.0359, sensor_height=0.0240,
                            x=0.0, y=0.0, z=0.0,
                            yaw=0.0, pitch=0.0, roll=0.0,
                            videofile=TEST_VIDEOS[test_video]))

    world.add_presentation(PresentationMap(world, map_id=1, height_pixels=500,
                                           width_pixels=500,
                                           extent=TEST_EXTENTS[test_video]))

    world.add_presentation(PresentationForecast(world, map_id=2,
                                                height_pixels=500,
                                                width_pixels=500,
                                                extent=TEST_EXTENTS[test_video]))

    world.add_presentation(PresentationLog(world, "Detection", "Detection.txt"))
    world.add_presentation(PresentationLog(world, "Pattern", "Pattern.txt"))
    world.add_presentation(PresentationLog(world, "Body", "Body.txt"))
    world.add_presentation(PresentationLog(world, "Event", "Event.txt"))

    world.run()

if __name__ == "__main__":
    run_application()
```

Demo

- 3-5 videos
- Program code

Pattern Filtering

Why pattern filtering?

- Reduces object detection (bounding box) noise
- Provides prediction for pattern location in the next frame (matching easier)
- Predicts pattern location when detection is missing

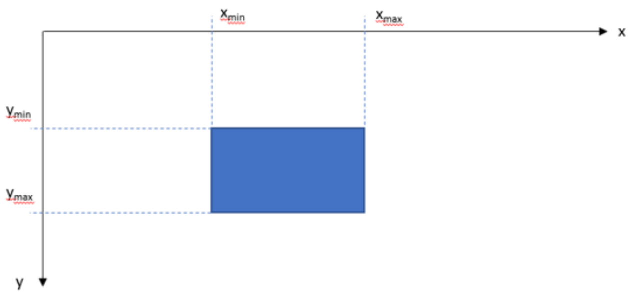
Hyperparameters:

```
#
PATTERN_ALFA = 200.0 # Pattern initial location error variance
PATTERN_BETA = 10000.0 # Pattern initial velocity error variance
PATTERN_C = np.array([[1.0, 0.0]]) # Pattern measurement matrix
PATTERN_Q = np.array([200.0]) # Pattern measurement variance
PATTERN_R = np.array([[0.1, 0.0],
                      [0.0, 1.0]]) # Pattern state equation covariance
#
```

Pattern Filtering

Pattern Kalman Filtering

Bounding box edge coordinates



Pattern location (bounding box) is determined by four edge coordinates: x_{min}, x_{max}, y_{min} and y_{max}. vx_{min}, vx_{max}, vy_{min} and vy_{max} are corresponding velocities.

Each edge coordinate is filtered separately and identically. x_{min} is used here as an example.

State equation in differential form:

$$\frac{d}{dt}\begin{bmatrix} x_{min}(t) \\ vx_{min}(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} * \begin{bmatrix} x_{min}(t) \\ vx_{min}(t) \end{bmatrix} + \epsilon(t)$$

State equation in difference form:

$$\begin{bmatrix} x_{min}(k+1) \\ vx_{min}(k+1) \end{bmatrix} = A * \begin{bmatrix} x_{min}(k) \\ vx_{min}(k) \end{bmatrix} + \varepsilon(k)$$

$$A = \begin{bmatrix} 1 & \Delta \\ 0 & 1 \end{bmatrix}$$

where Δ is the time increment and ε Gaussian noise with covariance R:

$$R = \begin{bmatrix} 0.1 & 0 \\ 0 & 1.0 \end{bmatrix}$$

Measurement equation

$$z(k) = C * \begin{bmatrix} x_{min}(k) \\ vx_{min}(k) \end{bmatrix} + \delta(k)$$

$$C = \begin{bmatrix} 1 & 0 \end{bmatrix}$$

where δ is Gaussian noise with covariance matrix Q:

$$Q = [200.0]$$

Kalman filter initialization:

$$\mu(0) = \begin{bmatrix} x_{min}(0) \\ 0 \end{bmatrix}$$

where x_{min} (0) is the first location measurement.

$$\Sigma(0) = \begin{bmatrix} 200.0 & 0 \\ 0 & 10\,000.0 \end{bmatrix}$$

Kalman filter update:

$$\mu_1(k) = A * \mu(k-1)$$

$$\Sigma_1(k) = A * \Sigma(k-1) * A^T + R$$

$$K(k) = \Sigma_1(k) * C^T * (C * \Sigma_1(k) * C^T + Q)^{-1}$$

$$\mu(k) = \mu_1(k) + K(k) * (z(k) - C * \mu_1(k))$$

$$\Sigma(k) = (I - K(k) * C) * \Sigma_1(k)$$

Pattern Filtering

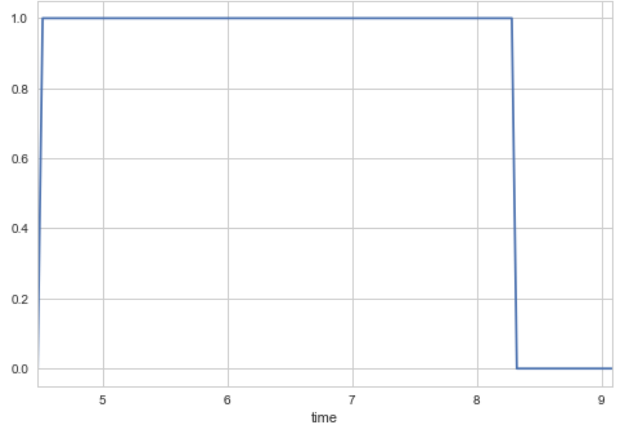
Event.txt

```
4.440,3,2061577943248,Detection created
4.440,2,2061579199488,Pattern removed
4.480,3,2061577756008,Detection created
4.480,3,2061577754272,Detection created
4.480,3,2061577755112,Detection created
4.480,1,2061577797816,Body created
4.480,2,2061577776432,Pattern created
4.520,3,2061577844944,Detection created
```

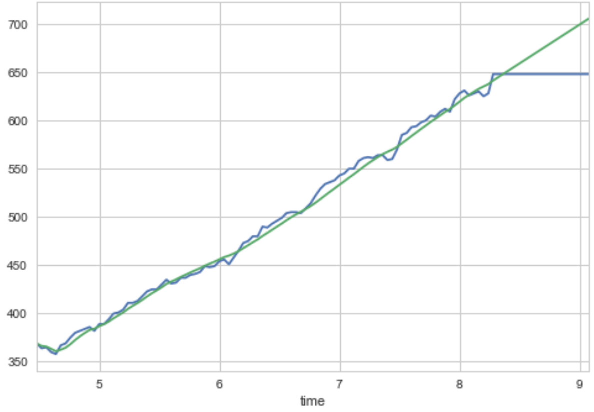
Pattern Filtering

Matched status, coordinate and velocity

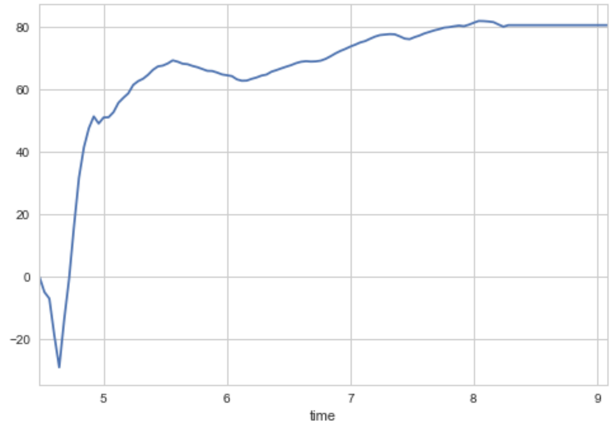
```
In [9]: data_one['matched'].plot()
Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x1b3759afe80>
```




```
In [10]: data_one['x_min_d'].plot() # blue, measurement
         data_one['x_min'].plot() # green, filtered + predicted
Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x1b376ccbe48>
```




```
In [11]: data_one['vx_min'].plot()
Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x1b376e50f98>
```

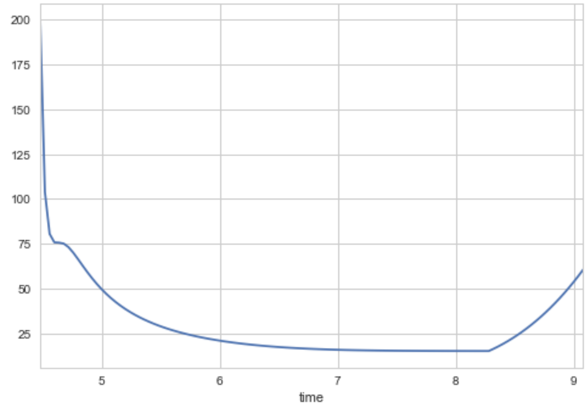


Pattern Filtering

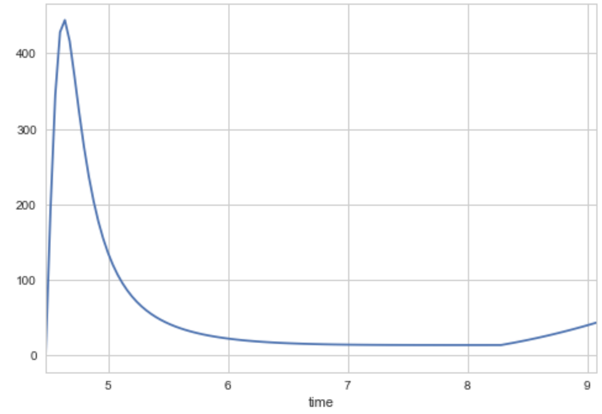
Covariance matrix

0=location, 1=velocity

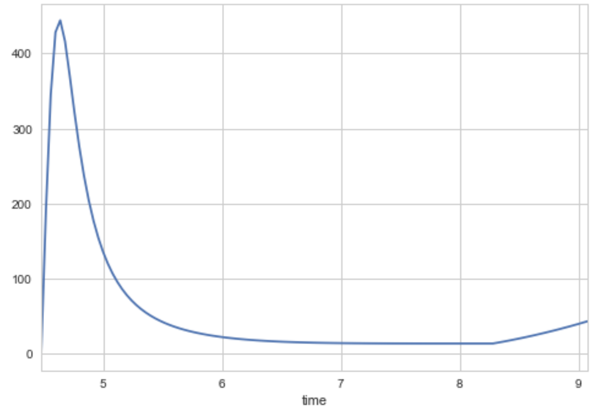
```
In [16]: data_one['sigma_x_min_00'].plot()
Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x1b3771859b0>
```



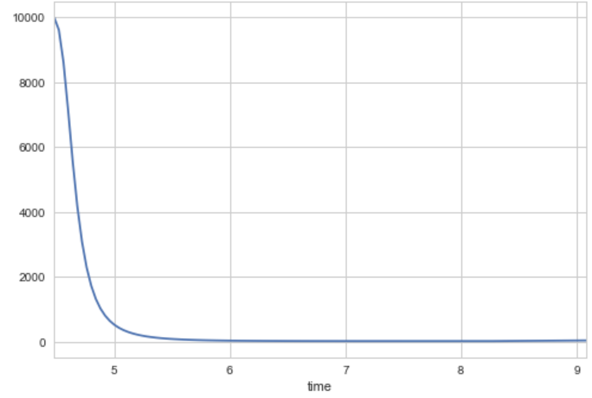

```
In [17]: data_one['sigma_x_min_01'].plot()
Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x1b37726b5c0>
```




```
In [18]: data_one['sigma_x_min_10'].plot()
Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x1b3772b9da0>
```




```
In [19]: data_one['sigma_x_min_11'].plot()
Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x1b377347358>
```



Matching / Confidence Level

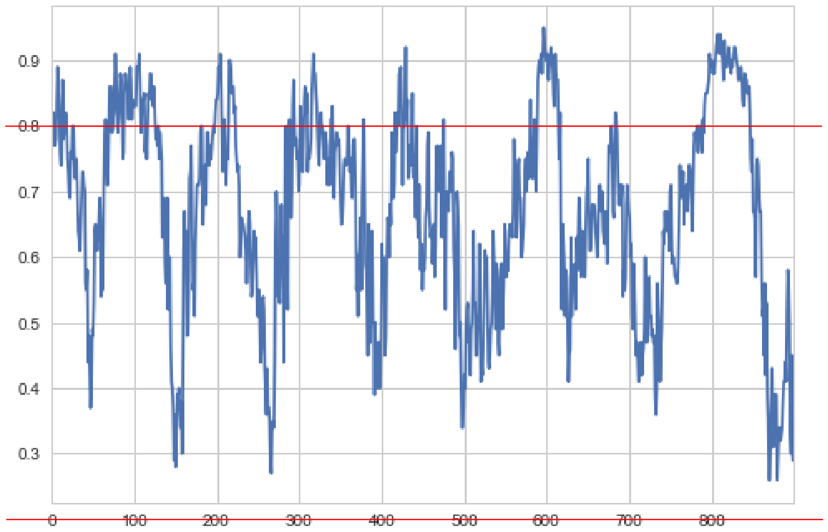
Minimum confidence level to create a pattern (and body) was varied between 0 and 1. The number of bodies created was compared to the true number of objects in the video.

	A	B	C	D	E	F	G	H	I	J
1	Objects detected		Confidence level							
2	Video	Correct	0,00	0,20	0,40	0,60	0,80	0,90	0,95	1,00
3	CarsOnHighway001.mpg	39	49	49	39	36	34	32	32	0
4	Calf-2679.mp4	1	2	2	2	2	1	1	1	0
5	Dunes-7238.mp4	1	7	7	6	5	2	2	2	0
6	Sofa-11294.mp4	1	2	2	1	1	1	1	1	0
7	Cars133.mp4	5	9	9	6	5	5	5	5	0
8	BlueTit2975.mp4	1	3	3	2	1	1	1	1	0
9	Railway-4106.mp4	1	10	10	5	3	3	1	1	0
10	Hiker1010.mp4	1	4	4	0	0	0	0	0	0
11	Cat-3740.mp4	1	3	3	2	2	1	1	1	0
12	SailingBoat6415.mp4	1	1	1	1	1	1	1	1	0
13	AWomanStandsOnTheSeashore-10058.mp4	1	1	1	1	1	1	1	1	0
14	Dog-4028.mp4	1	4	4	2	1	1	1	1	0
15	Boat-10876.mp4	1	2	2	1	1	1	1	0	0
16	Horse-2980.mp4	1	3	3	3	2	2	1	1	0
17	Sheep-12727.mp4	1	1	1	1	1	1	1	1	1

Good value for creating a new pattern is between 0.8 and 0.9.

Matching / Confidence Level

Confidence level has dynamics



create

update

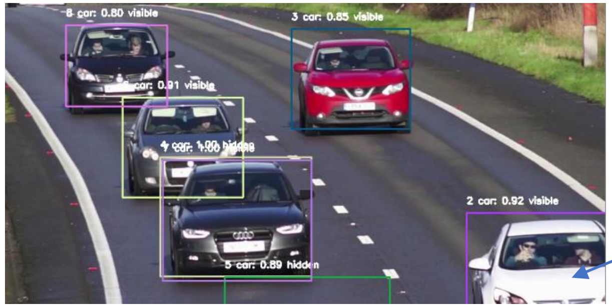
ignore

Different levels for creating and updating image object.
Hyperparameters:

- CONFIDENCE_LEVEL_CREATE (0.8)
- CONFIDENCE_LEVEL_UPDATE (0.2)

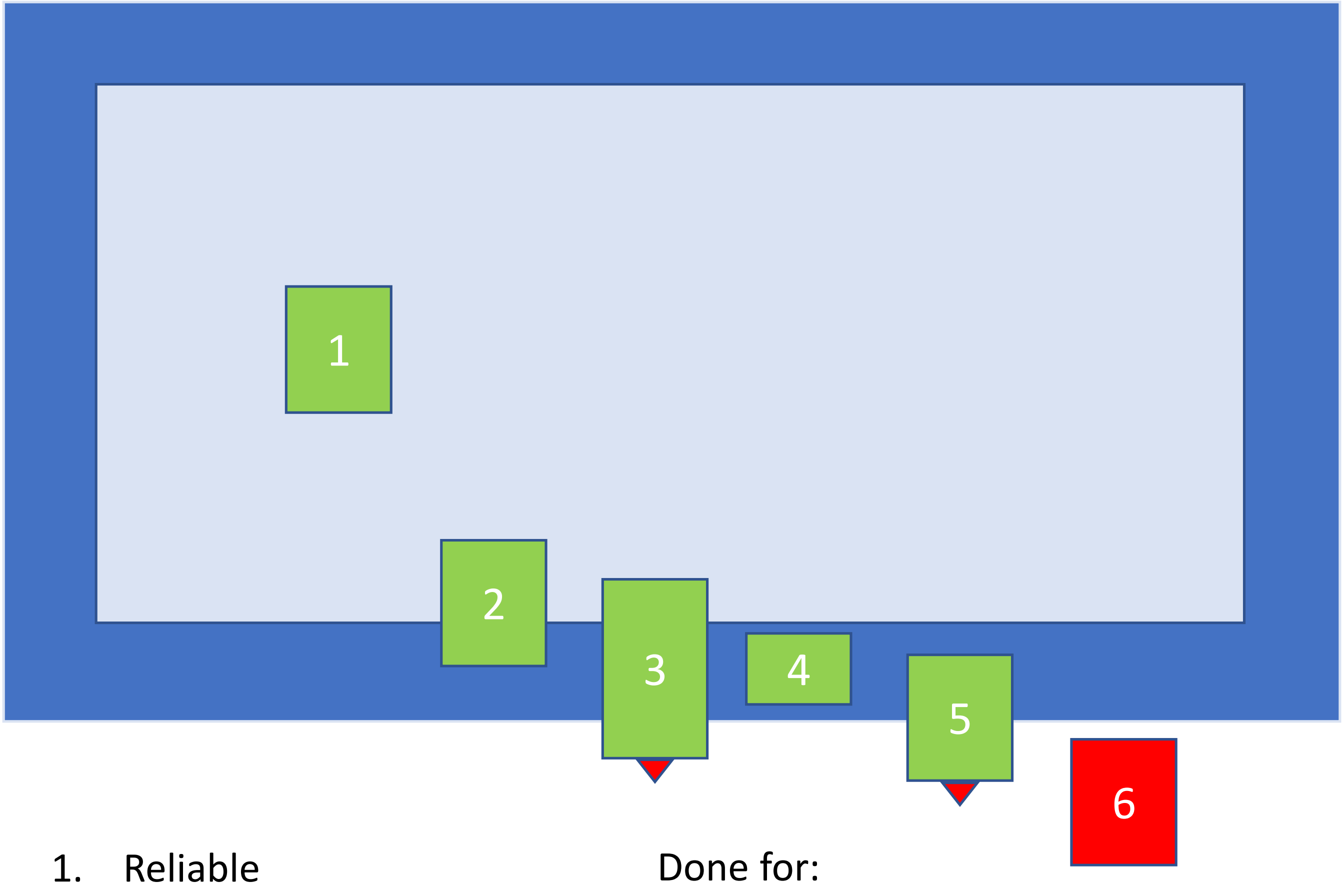
Matching / Border Behaviour

The problem:
Bounding box size and form are distorded near edges



Hyperparameter BORDER_WIDTH (30)

Matching / Border Behaviour



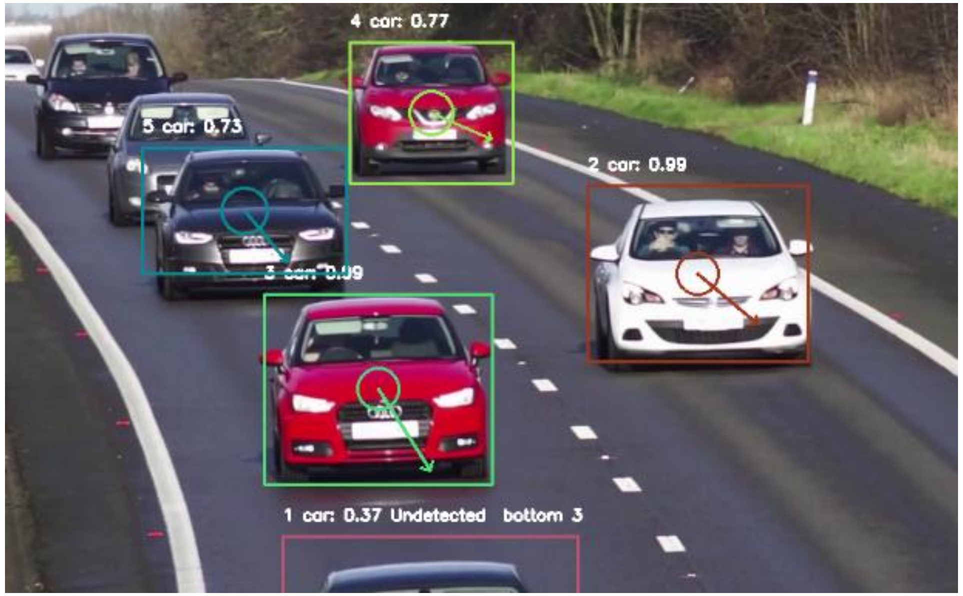
1. Reliable
2. Reliable
3. Unreliable
4. Reliable, not created
5. Unreliable, not created
6. Unreliable, removed

Done for:

- left
- right
- top
- bottom

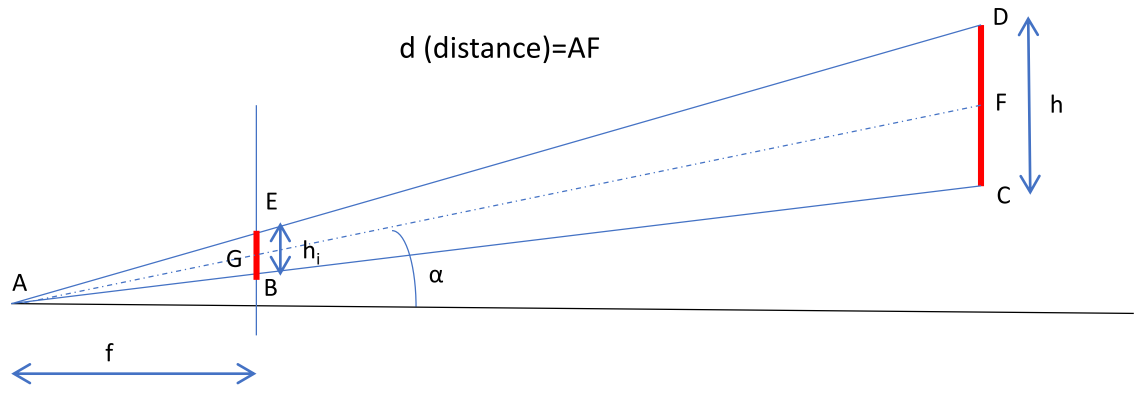
If a pattern touches 3 borders, it is removed
Reliable = body information updated

Matching / Pattern Retention



Patterns are removed if not detected in RETENTION_COUNT_MAX (30) successive frames.

Distance Estimation



Similar triangles AGE and AFD:

$$\frac{0.5 * h_i}{0.5 * h} = \frac{AG}{d} = \frac{\frac{f}{\cos(\alpha)}}{d} = \frac{f}{d * \cos(\alpha)}$$

$$d = \frac{f * h}{\cos(\alpha) * h_i}$$

Distance Estimation

Similar equations for horizontal direction (β=azimuth):

$$d = \frac{f * l}{\cos(\alpha) * \cos(\beta) * l_i} = \frac{f * l}{\cos(\alpha) * \cos(\beta) * l_i * s_h/p_h}$$

s_w= *sensor width (m)*
s_h= *sensor height (m)*
p_w= *image width (pixels)*
p_h= *image height (pixels)*
l_i = *object length (pixels)*
l = object length (m)
f = focal length (m)
α = *altitude (rad)*
β = *azimuth (rad)*

Assumptions:

- *equal vertical/horizontal pixel spacing*
- *optical axis in image center*

Example (Nikon D800E):

s_w= sensor width (m) = 0.0359 m
s_h= sensor height (m) = 0.0240 m
p_w= image width (pixels) = 7360
p_h= image height (pixels) = 4912
h_i = object height (pixels) = 100
h = object height (m) = 1.0 m
f = focal length (m) = 0.050 m
α = *altitude (rad) = 0.0*
β = *azimuth (rad) = 0.0*

$$d = \frac{0.050m * 1m}{1.0*1.0*100 * 0.024m/4912} = 102.33\ m$$

Distance Estimation

Question: How to compare pattern and body sizes for distance estimation?

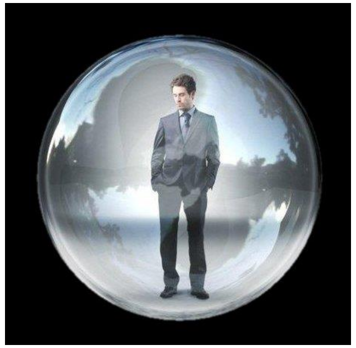
Height or width alone might be misleading.

Some form of (3D) spatial simplification is needed, like

- cube
- rectangular prism
- cylinder
- sphere (probably the easiest math)

Uncertainty should be modeled.

Solution:
pattern circle <---> body sphere



Distance Estimation

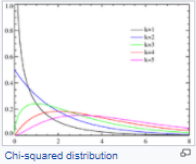
Body radius distribution

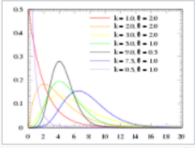
Distibution should

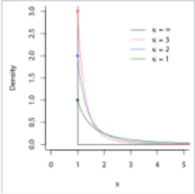
- be defined in [0,∞]
- mode > 0
- simple
- skew controllable

Supported on semi-infinite intervals, usually [0,∞) [edit]

- The Beta prime distribution
- The Birnbaum–Saunders distribution, also known as the fatigue life distribution, is a probability distribution used extensively in reliability applications to model failure times.
- The chi distribution
  - The noncentral chi distribution
- The chi-squared distribution, which is the sum of the squares of *n* independent Gaussian random variables. It is a special case of the Gamma distribution, and it is used in goodness-of-fit tests in statistics.
  - The inverse-chi-squared distribution
  - The noncentral chi-squared distribution
  - The Scaled inverse chi-squared distribution
- The Dagum distribution
- The exponential distribution, which describes the time between consecutive rare random events in a process with no memory.
- The Exponential-logarithmic distribution
- The F-distribution, which is the distribution of the ratio of two (normalized) chi-squared-distributed random variables, used in the analysis of variance. It is referred to as the beta prime distribution when it is the ratio of two chi-squared variates which are not normalized by dividing them by their numbers of degrees of freedom.
  - The noncentral F-distribution
- The folded normal distribution
- The Fréchet distribution
- The Gamma distribution, which describes the time until *n* consecutive rare random events occur in a process with no memory.
  - The Erlang distribution, which is a special case of the gamma distribution with integral shape parameter, developed to predict waiting times in queuing systems
  - The inverse-gamma distribution
- The Generalized gamma distribution
- The generalized Pareto distribution
- The Gamma/Gompertz distribution
- The Gompertz distribution
- The half-normal distribution
- Hotelling's T-squared distribution
- The inverse Gaussian distribution, also known as the Wald distribution
- The Lévy distribution
- The log-Cauchy distribution
- The log-Laplace distribution
- The log-logistic distribution
- The log-normal distribution, describing variables which can be modelled as the product of many small independent positive variables.
- The Lomax distribution
- The Mittag-Leffler distribution
- The Nakagami distribution
- The Pareto distribution, or "power law" distribution, used in the analysis of financial data and critical behavior.
- The Pearson Type III distribution
- The Phase-type distribution, used in queueing theory
- The phased bi-exponential distribution is commonly used in pharmokinetics
- The phased bi-Weibull distribution
- The Rayleigh distribution
- The Rayleigh mixture distribution
- The Rice distribution
- The shifted Gompertz distribution
- The type-2 Gumbel distribution
- The Weibull distribution or Rosin Rammler distribution, of which the exponential distribution is a special case, is used to model the lifetime of technical devices and is used to describe the particle size distribution of particles generated by grinding, milling and crushing operations.


Chi-squared distribution

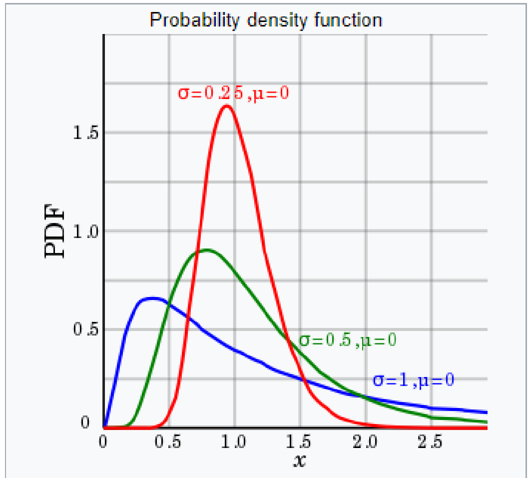

Gamma distribution


Pareto distribution

Distance Estimation

Log-normal distribution for body radius

Log-normal



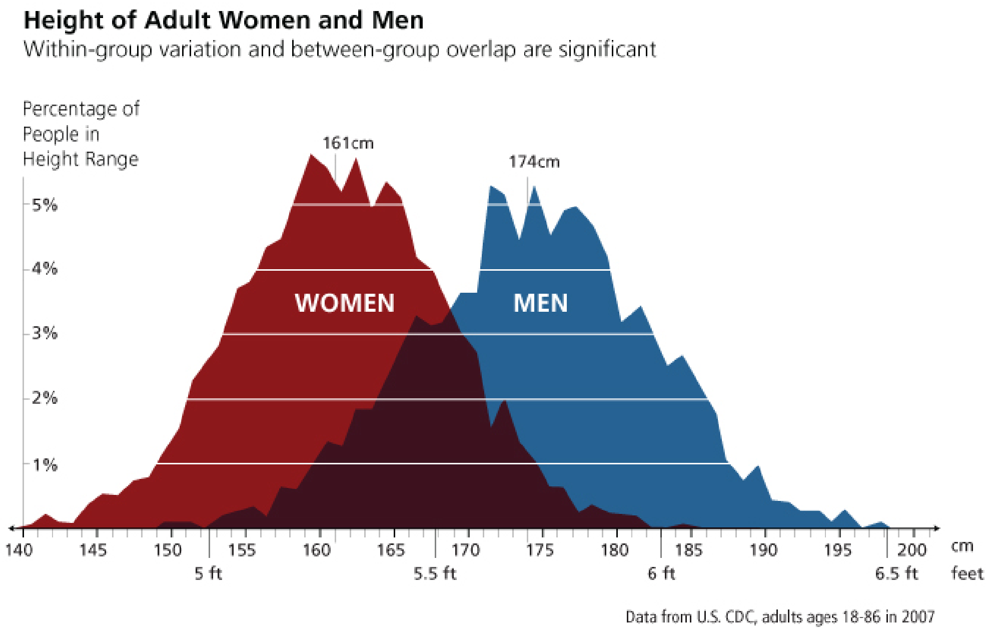
Some log-normal density functions with identical parameter μ but differing parameters σ

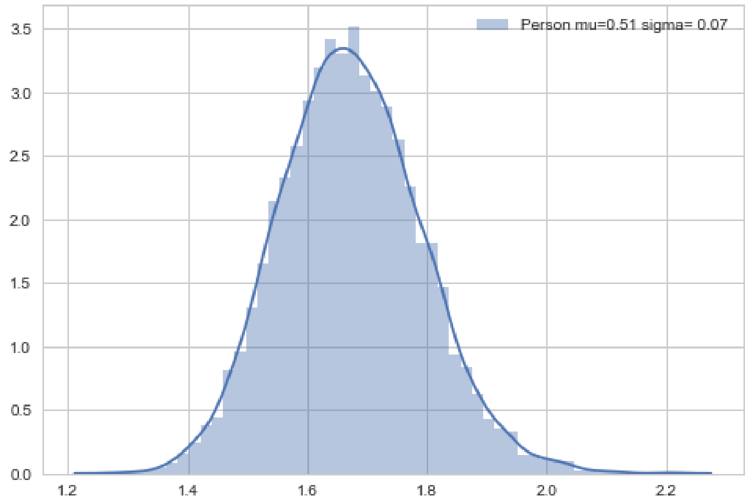
Used in the context of describing human height distribution

Notation	$\mathrm{Lognormal}(\mu,\, \sigma^2)$
Parameters	$\mu \in (-\infty, +\infty)$, $\sigma > 0$
Support	$x \in (0, +\infty)$
PDF	$\frac{1}{x\sigma\sqrt{2\pi}}\, e^{-\frac{(\ln x-\mu)^2}{2\sigma^2}}$
CDF	$\frac{1}{2} + \frac{1}{2}\,\mathrm{erf}\left[\frac{\ln x - \mu}{\sqrt{2}\sigma}\right]$
Mean	$\exp\left(\mu + \frac{\sigma^2}{2}\right)$
Median	$\exp(\mu)$
Mode	$\exp(\mu - \sigma^2)$
Variance	$[\exp(\sigma^2) - 1]\exp(2\mu + \sigma^2)$
Skewness	$(e^{\sigma^2} + 2)\sqrt{e^{\sigma^2} - 1}$
Ex. kurtosis	$\exp(4\sigma^2) + 2\exp(3\sigma^2) + 3\exp(2\sigma^2) - 6$
Entropy	$\log(\sigma e^{\mu+\frac{1}{2}}\sqrt{2\pi})$
MGF	defined only for numbers with a non-positive real part, see text
CF	representation $\sum_{n=0}^{\infty}\frac{(it)^n}{n!}e^{n\mu+n^2\sigma^2/2}$ is asymptotically divergent but sufficient for numerical purposes
Fisher information	$\begin{pmatrix} 1/\sigma^2 & 0 \\ 0 & 1/2\sigma^4 \end{pmatrix}$

Distance Estimation

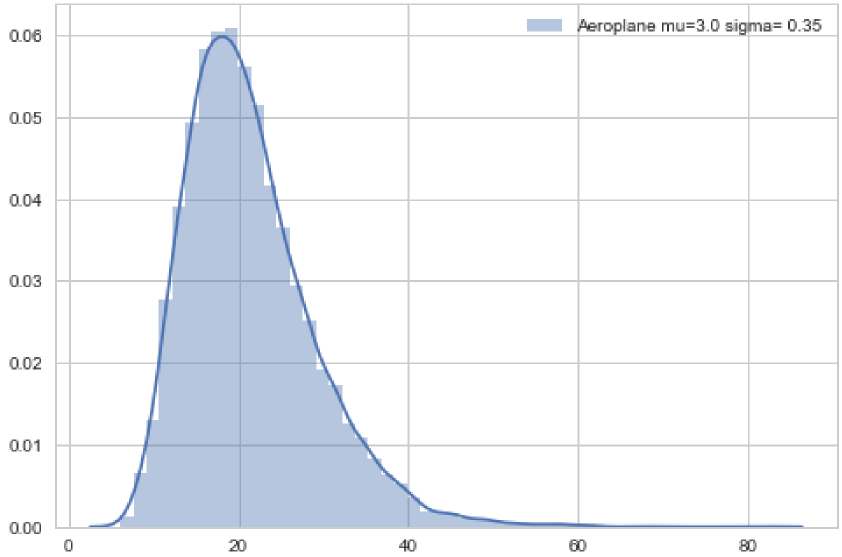
Example: Person

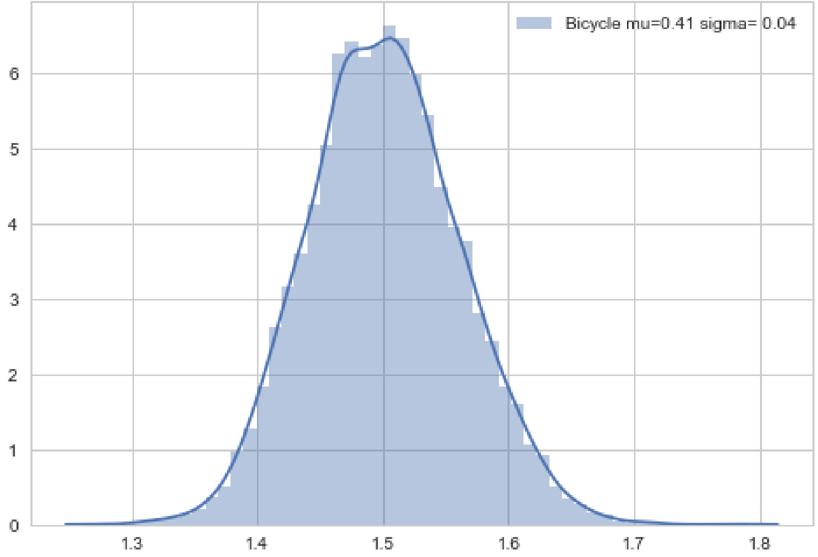




Distance Estimation

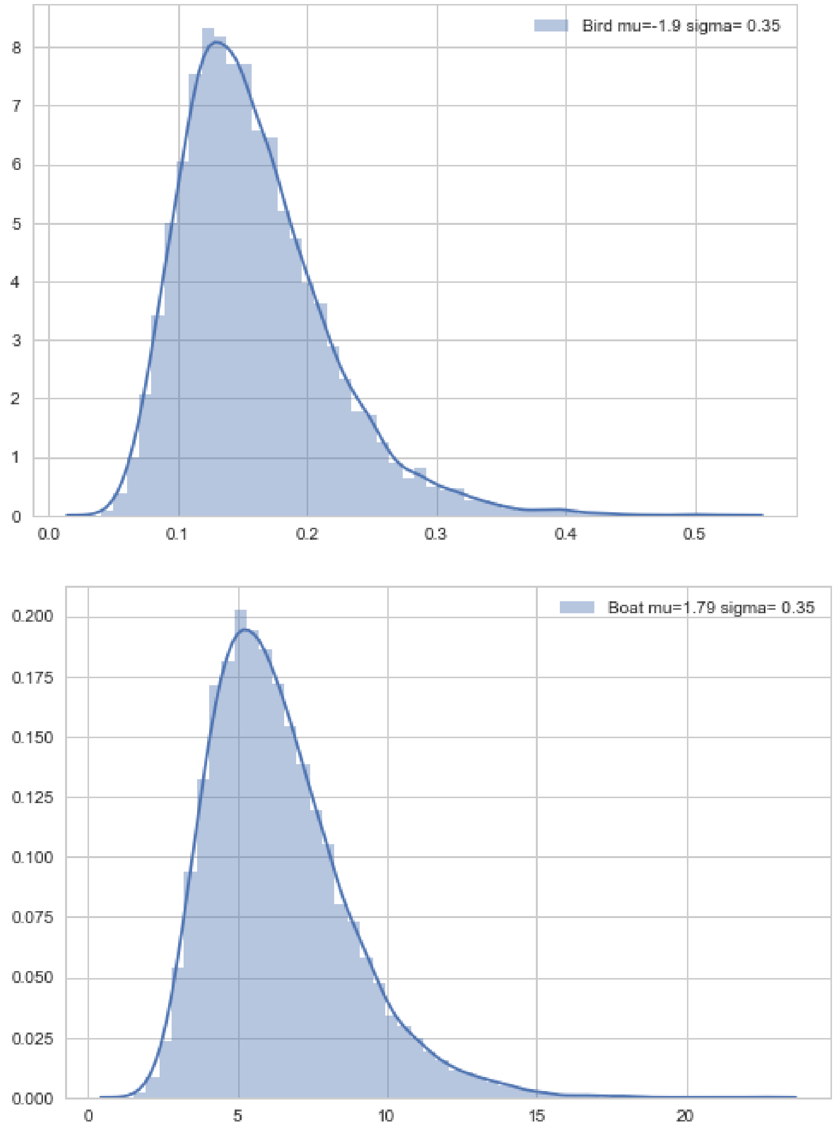
Bubble diameters (2*radius)





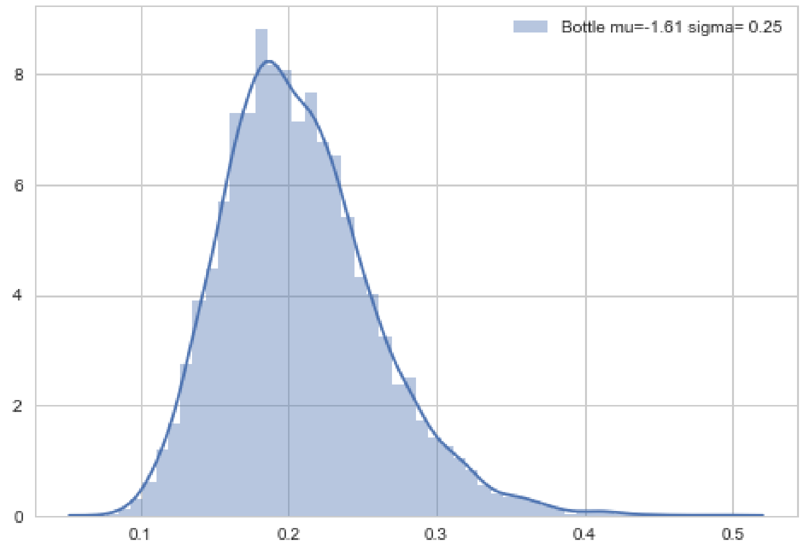
Distance Estimation

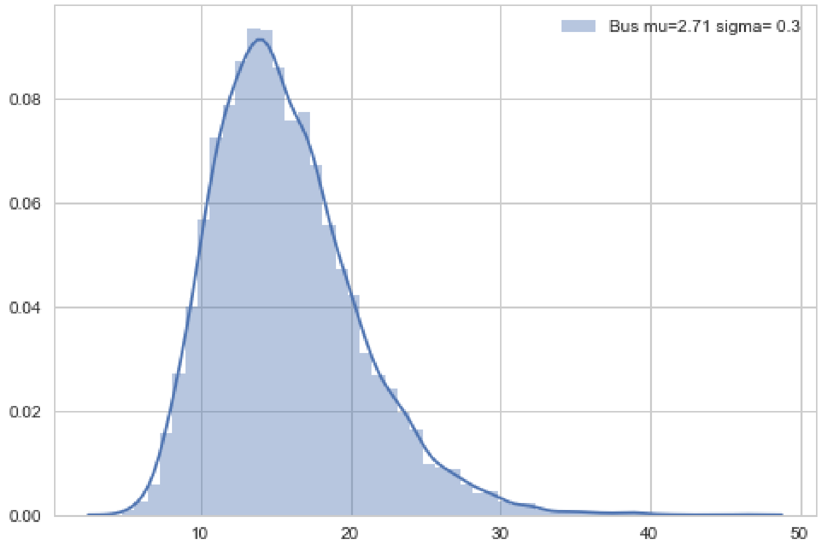
Bubble diameters (2*radius)



Distance Estimation

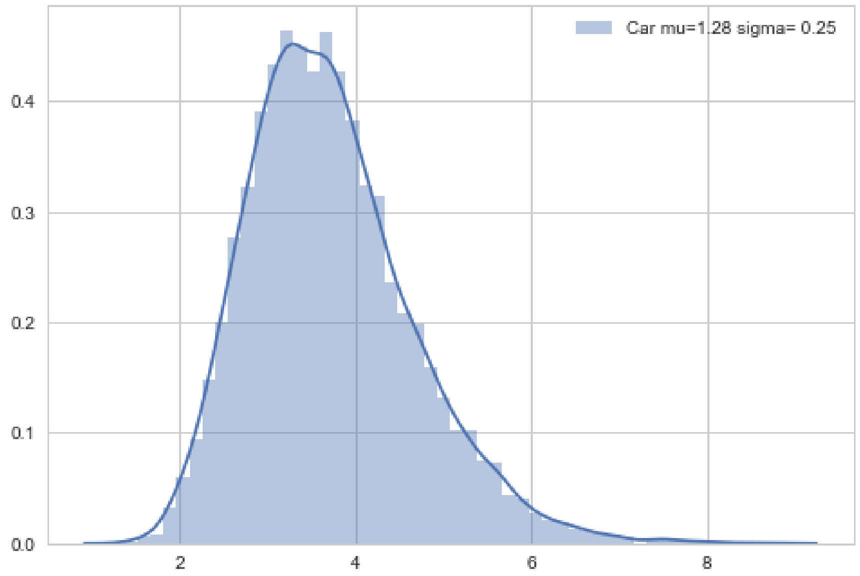
Bubble diameters (2*radius)

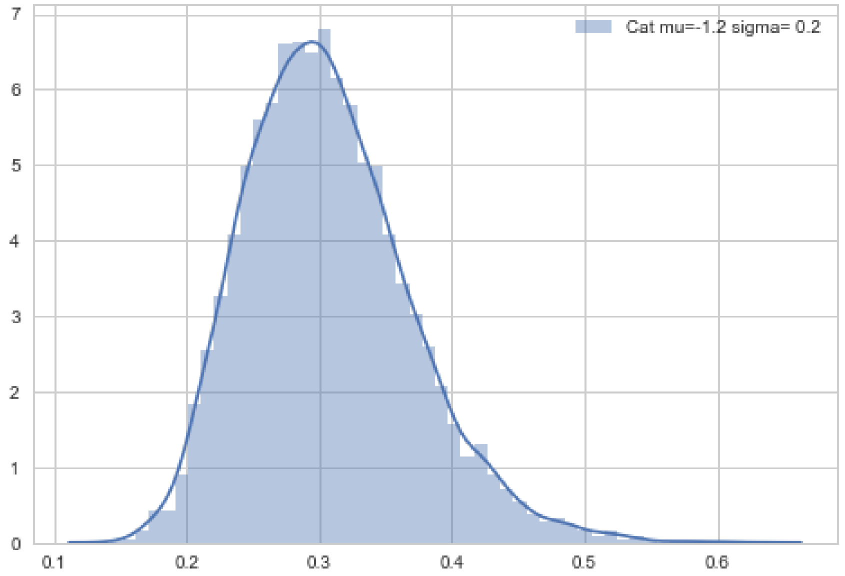




Distance Estimation

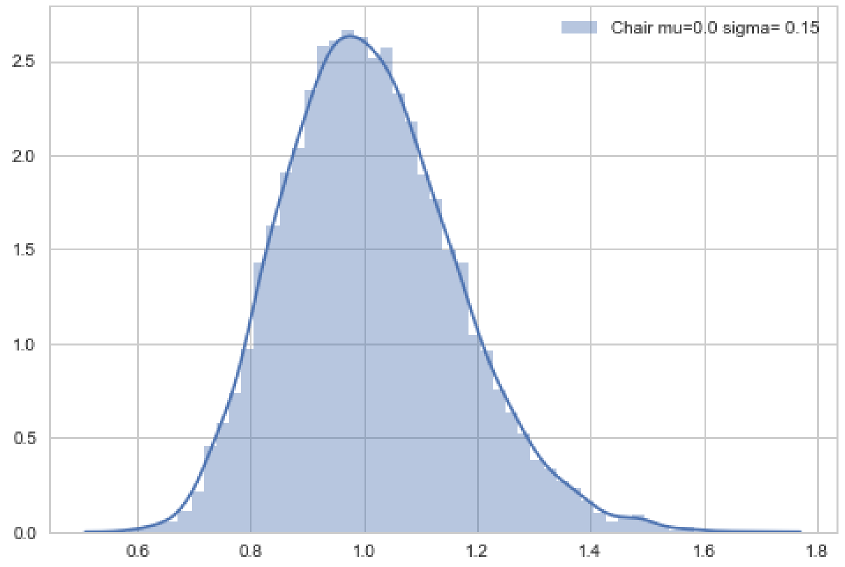
Bubble diameters (2*radius)

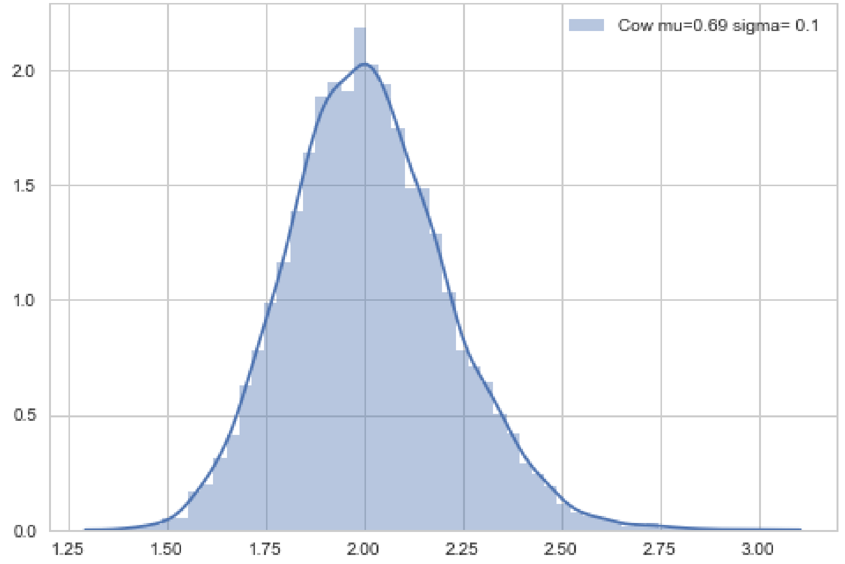




Distance Estimation

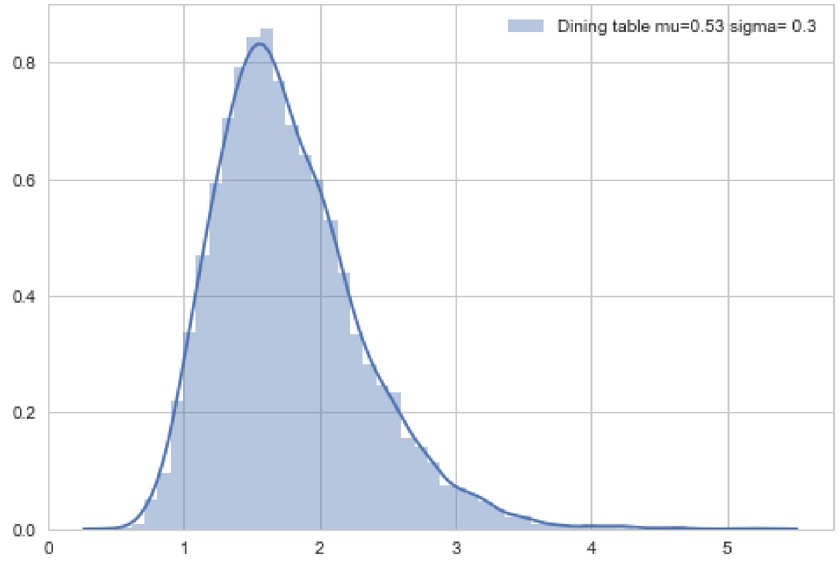
Bubble diameters (2*radius)

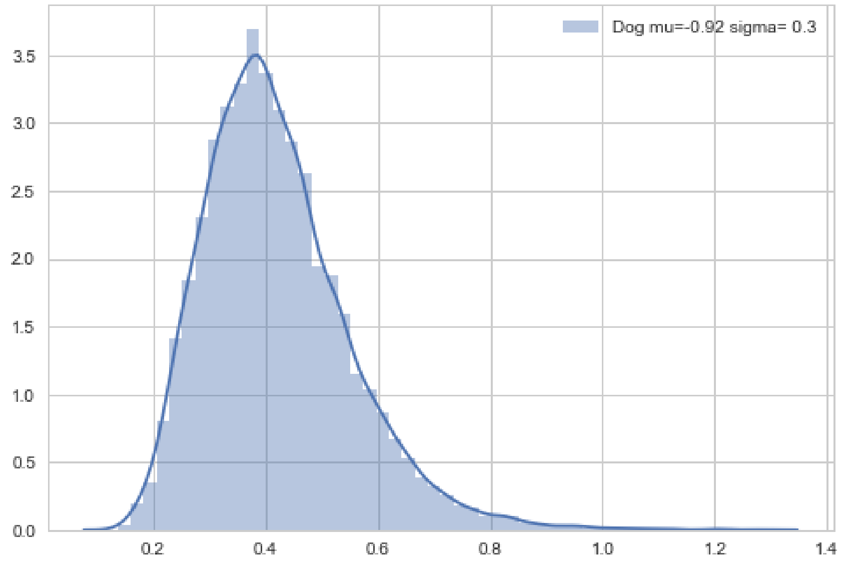




Distance Estimation

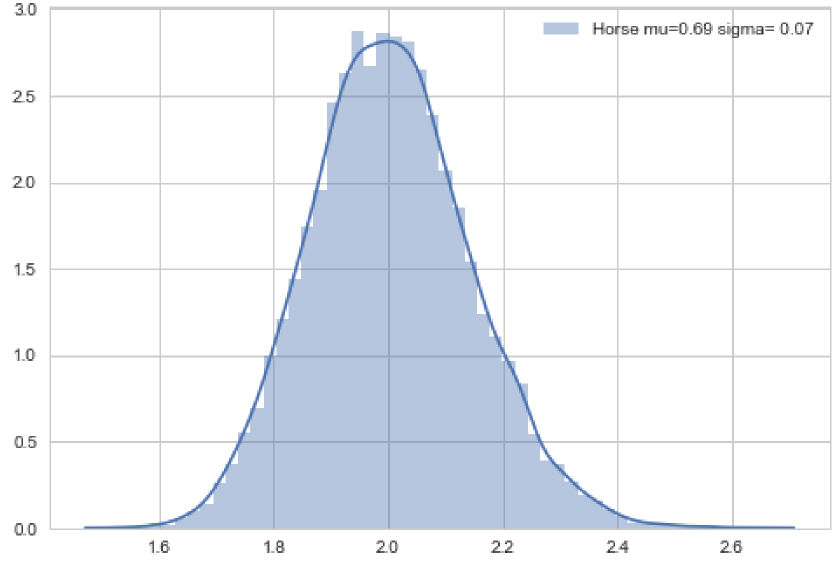
Bubble diameters (2*radius)

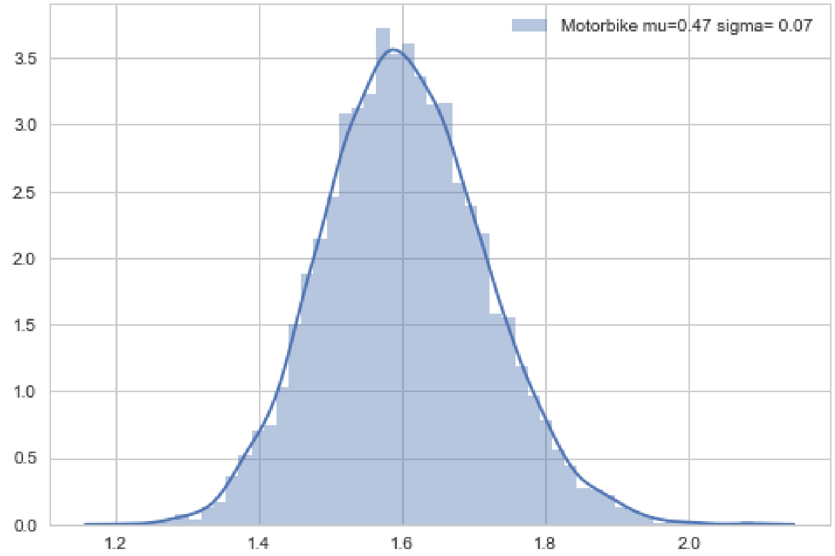




Distance Estimation

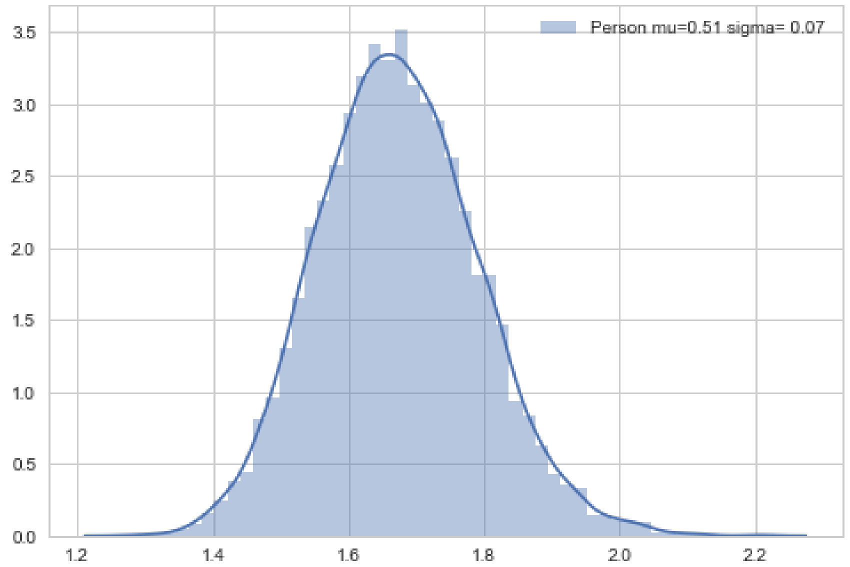
Bubble diameters (2*radius)

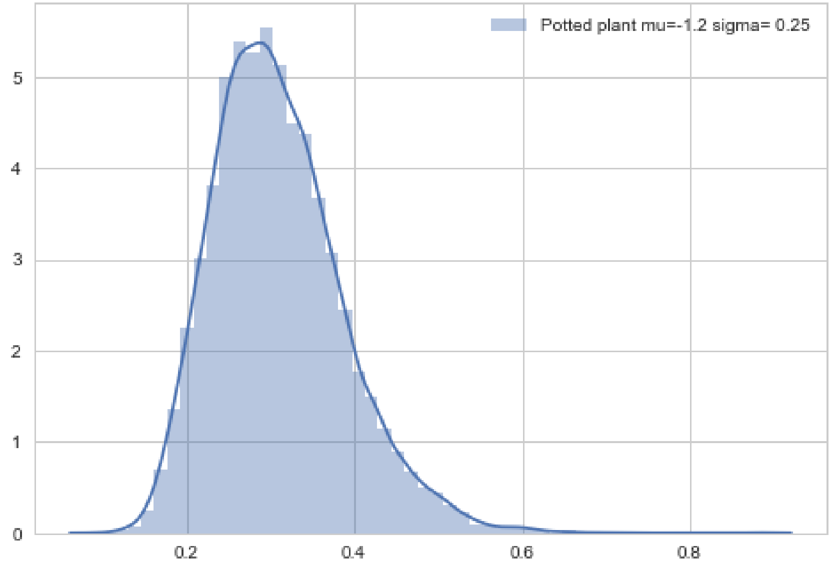




Distance Estimation

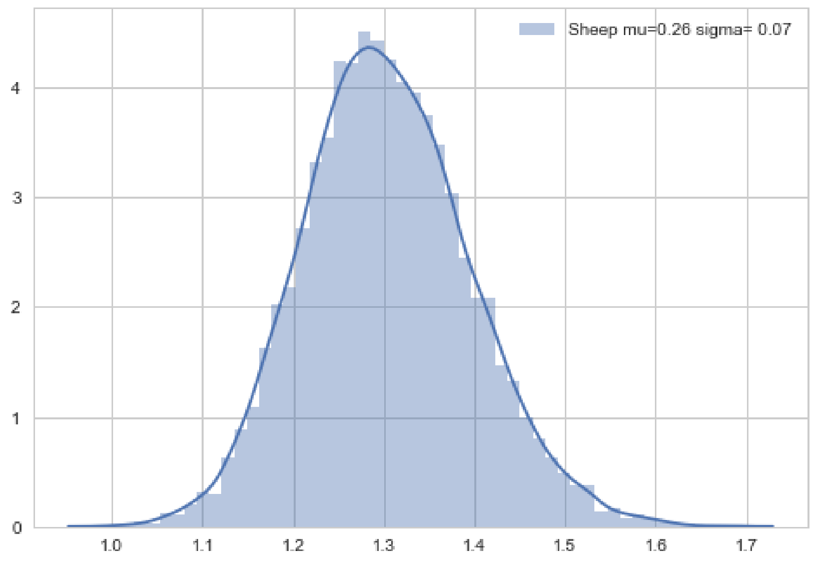
Bubble diameters (2*radius)

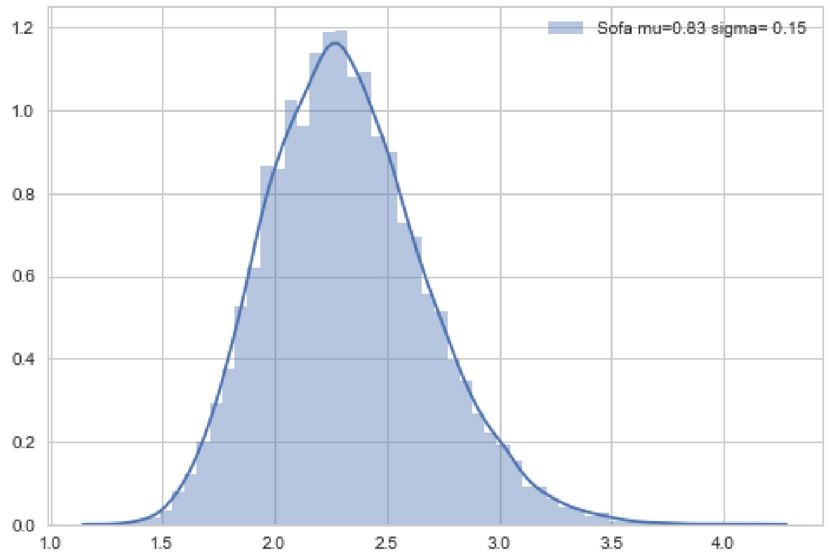




Distance Estimation

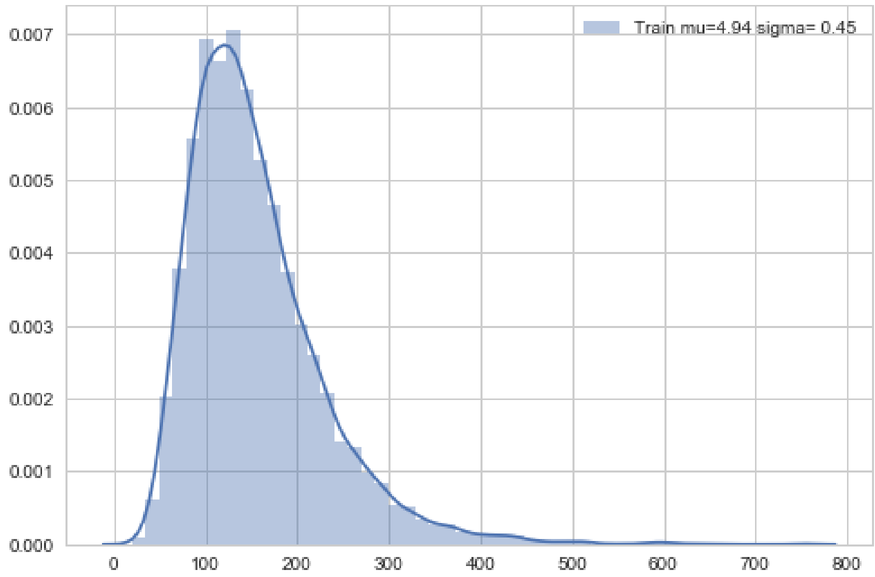
Bubble diameters (2*radius)

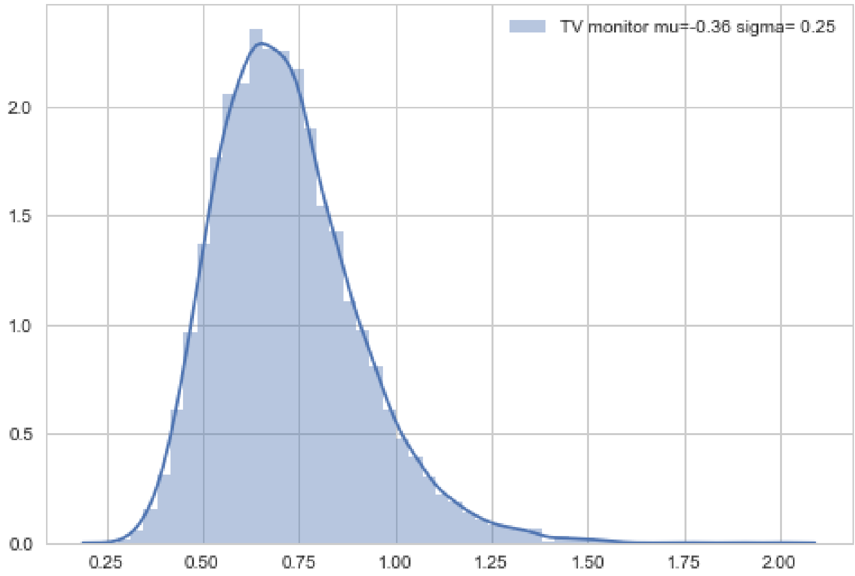




Distance Estimation

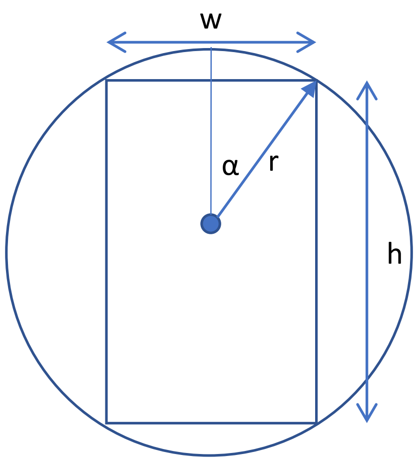
Bubble diameters (2*radius)





Distance Estimation

Radius of enclosing circle will be used for pattern



From bounding box coordinates to radius:

$$r = \sqrt{(\frac{w}{2})^2 + (\frac{h}{2})^2}$$

$$h = (ymax - ymin) \quad c_y = (ymax + ymin)/2$$

$$w = (xmax - xmin) \quad c_x = (xmax + xmin)/2$$

Distance Estimation

Distance estimation using pattern circle and body sphere

$$d = \frac{f * r}{\cos(\alpha) * \cos(\beta) * r_i * s_h / p_h}$$

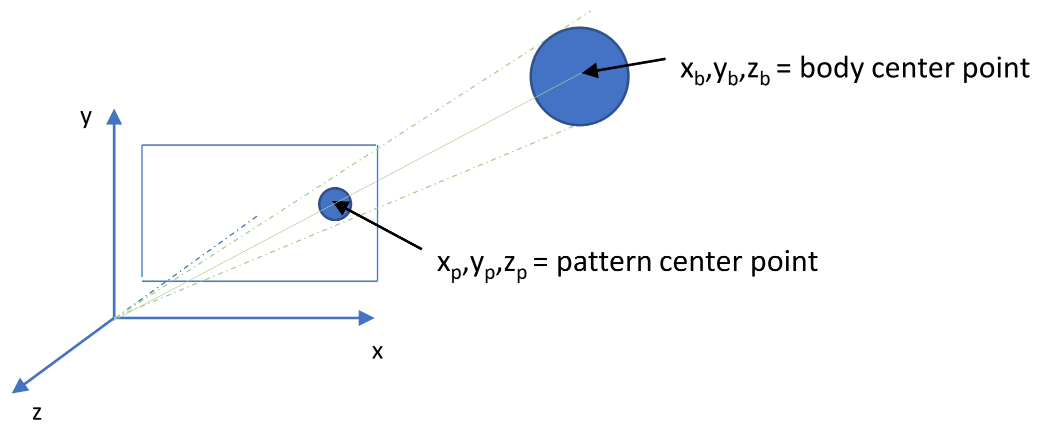
$s_h = sensor\ height\ (m)$
p_h = *image height (pixels)*
r_i = *pattern radius (pixels)*
r = body radius (m), mean from class specific distribution
f = focal length (m)
α = *altitude (rad)*
β = *azimuth (rad)*

Distance Estimation

Remarks:

- Video metadata often lacks sensor and focal parameters
- Focal length can change during shooting (zooming)

3D Projection



From pixel coordinates x_p, y_p (sensor plane) to 3d camera coordinates:

$$(x_p, y_p, z_p) = \left(-\frac{s_w}{2} + x_p * \frac{s_w}{p_w},\ \ \frac{s_h}{2} - y_p * \frac{s_h}{p_h},\ -f\right)$$

$s_w = sensor\ width\ (m)$
$s_h = sensor\ height\ (m)$
p_w = *image width (pixels)*
p_h = *image height (pixels)*
h_i = *object height (pixels)*
h = *object height (m)*
f = *focal length (m)*
α = *altitude (rad)*

Body center will be on the line:

$$(x_b, y_b, z_b) = t * (x_p, y_p, z_p)$$

The distance to the body is:

$$d = \frac{f * h}{\cos(\alpha) * \cos(\beta) * h_i * s_h / p_h}$$

$$\alpha = \arctan(y_p/f)$$
$$\beta = \arctan(x_p/f)$$

3D Projection

So: $t^2 * ({x_p}^2 + {y_p}^2 + {z_p}^2) = d^2$

Solving for t: $$t = \frac{d}{\sqrt{{x_p}^2 + {y_p}^2 + {z_p}^2}}$$

$(x_b, y_b, z_b) = t * (x_p, y_p, z_p)$

Where:

$(x_p, y_p, z_p) = (-\frac{s_w}{2} + x_p * \frac{s_w}{p_w}, \ \frac{s_h}{2} - y_p * \frac{s_h}{p_h}, \ -f)$

$$t = \frac{d}{\sqrt{{x_p}^2 + {y_p}^2 + {z_p}^2}}$$

$$d = \frac{f * h}{\cos(\alpha) * \cos(\beta) * h_i * s_h / p_h}$$

3D Projection

Example:

s_w= sensor width (m) = 0.0359 m
s_h= sensor height (m) = 0.0240 m
p_w= image width (pixels) = 7360
p_h= image height (pixels) = 4912
r_i = pattern radius (pixels) = 100
r = body radius (m) = 1.0 m
f = focal length (m) = 0.050 m
x_p = 1200
y_p = 2000

$(x_p, y_p, z_p) = (-\frac{s_w}{2} + xp * \frac{s_w}{p_w},\ \frac{s_h}{2} - yp * \frac{s_h}{p_h},\ -f)$

$= (-\frac{0.0359}{2} + 1200 * \frac{0.0359}{7360},\ \frac{0.0240}{2} - yp * \frac{0.0240}{4912},\ -0.050) = (-0.0121, 0.0022, -0.0500)$

$\alpha = \arctan(y_p/f) = 0.0445 \qquad \beta = \arctan(x_p/f) = -0.2374$

$$d = \frac{f * h}{\cos(\alpha) * \cos(\beta) * h_i * s_h/p_h} = \frac{0.050 * 1}{\cos(0.0445) * \cos(-0.2374) * 100 * 0.0240/4912} = 105.39$$

$$t = \frac{105.39}{\sqrt{-0.0121^2 + 0.0022^2 + -0.0500^2}} = 2.0468e+03$$

$(x_b, y_b, z_b) = t * (x_p, y_p, z_p) = 2.0468e+03 * (-0.0121, 0.0022, -0.0500) = (-24.7593, 4.5602, -102.3389)$

Body Filtering

General

- Enables prediction, including collision detection
- Second order model does not work, constant acceleration makes bodies bounce back or get enormous velocities
- In world, constant acceleration for several (tens) of seconds is not common
- First order model works! (No wonder it’s popular in robotics…)
- When measurement is lost, the body is switched into constant velocity mode

Body Filtering

Body Kalman Filtering

Body center point location

State vector s:

$$s = \begin{bmatrix} x \\ y \\ z \\ v_x \\ v_y \\ v_z \end{bmatrix}$$

where

(x, y, z) = location of the body center point

(v_x , v_y , v_z) = velocity of the body

State equation in differential form:

$$\frac{ds(t)}{dt} = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} * s(t) + \epsilon(t)$$

Body Filtering

State equation in difference form:

$$s(k+1) = \left(I + \Delta * \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \right) * s(k) + \epsilon(k) = A * s(k) + \varepsilon(k)$$

$$A = \begin{bmatrix} 1 & 0 & 0 & \Delta & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

where Δ is the time increment and ε Gaussian noise with covariance R:

$$R = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Measurement equation:

$$z(k) = C * s(k) + \delta(k)$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

Where δ is Gaussian noise with covariance matrix Q:

$$Q = \begin{bmatrix} 200 & 0 & 0 \\ 0 & 200 & 0 \\ 0 & 0 & 200 \end{bmatrix}$$

Body Filtering

Kalman filter initialization:

$$\mu(0) = \begin{bmatrix} x(0) \\ y(0) \\ z(0) \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

where x(0), y(0), z(0) is the first location measurement.

$$\Sigma(0) = \begin{bmatrix} 100\,000 & 0 & 0 & 0 & 0 & 0 \\ 0 & 100\,000 & 0 & 0 & 0 & 0 \\ 0 & 0 & 100\,000 & 0 & 0 & 0 \\ 0 & 0 & 0 & 100\,000 & 0 & 0 \\ 0 & 0 & 0 & 0 & 100\,000 & 0 \\ 0 & 0 & 0 & 0 & 0 & 100\,000 \end{bmatrix}$$

Kalman filter update:

$$\mu_1(k) = A * \mu(k-1)$$

$$\Sigma_1(k) = A * \Sigma(k-1) * A^T + R$$

$$K(k) = \Sigma_1(k) * C^T (C * \Sigma_1(k) * C^T + Q)^{-1}$$

$$\mu(k) = \mu_1(k) + K(k) * (z(k) - C * \mu_1(k))$$

$$\Sigma(k) = (I - K(k) * C) * \Sigma_1(k)$$

Body Filtering

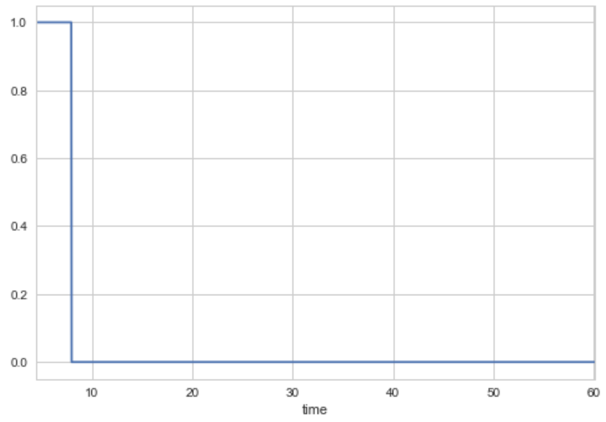
Example 1

Event.txt

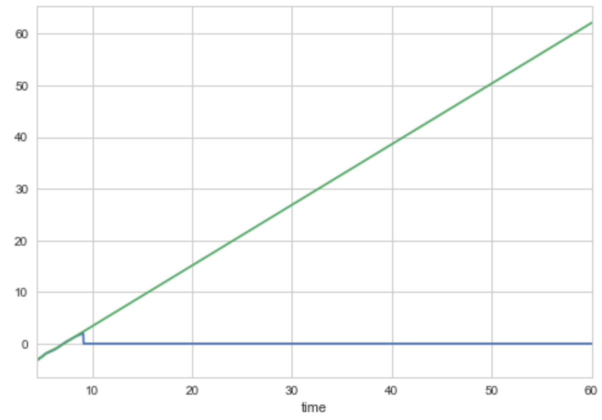
```
4.440,3,2061577943248,Detection created
4.440,2,2061579199488,Pattern removed
4.480,3,2061577756008,Detection created
4.480,3,2061577754272,Detection created
4.480,3,2061577755112,Detection create
4.480,1,2061577797816,Body created
4.480,2,2061577776432,Pattern created
4.520,3,2061577844944,Detection created
```

Body Filtering

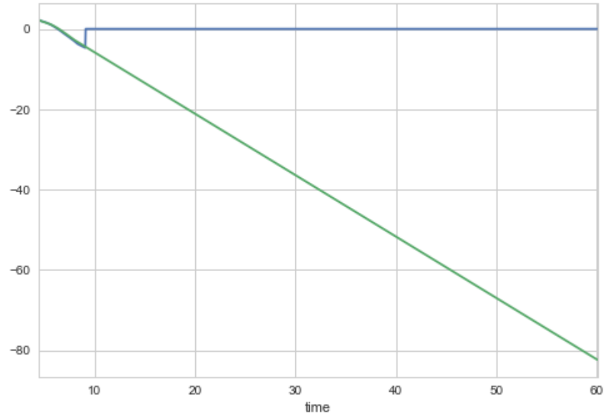
```
In [5]: data_one['status'].plot()

Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x2e5b3fa4e10>
```



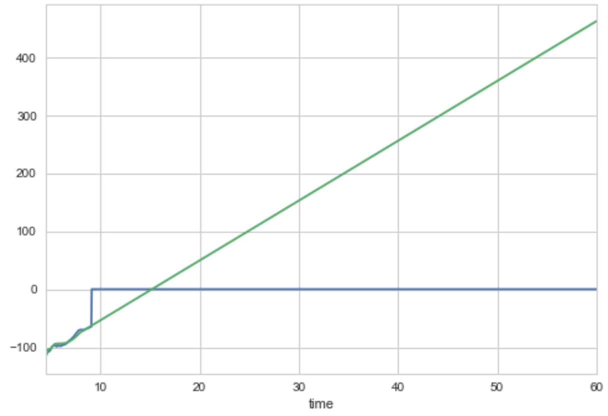

```
In [7]: data_one['x_pattern'].plot() # blue, measurement
        data_one['x'].plot() # green, filtered + predicted

Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x2e5b4111c50>
```




```
In [8]: data_one['y_pattern'].plot() # blue, measurement
        data_one['y'].plot() # green, filtered + predicted

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x2e5b4125470>
```

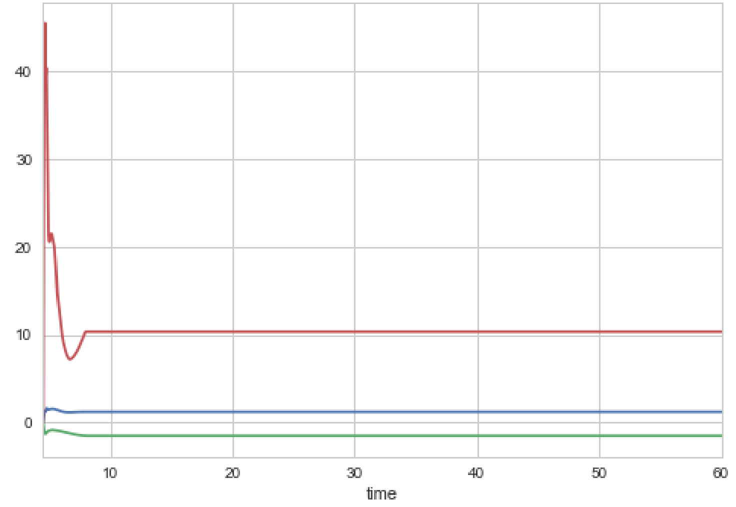



```
In [9]: data_one['z_pattern'].plot() # blue, measurement
        data_one['z'].plot() # green, filtered + predicted

Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x2e5b41ab6d8>
```

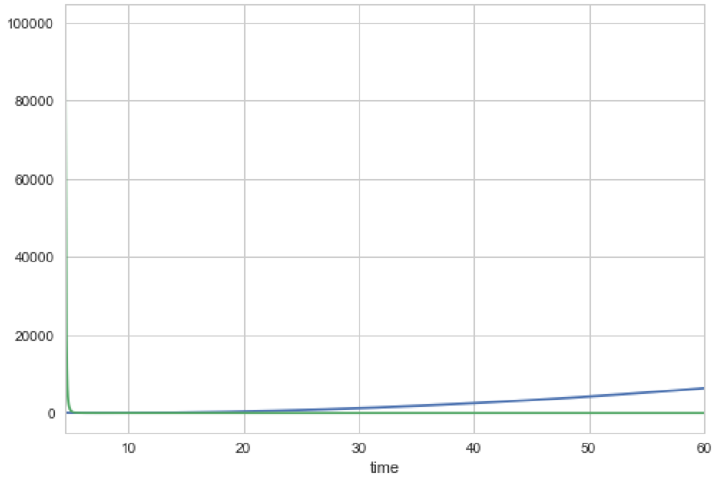


Body Filtering

```
In [10]: data_one['vx'].plot() # blue
         data_one['vy'].plot() # green
         data_one['vz'].plot() # red

Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x2e5b424cac8>
```




```
In [11]: data_one['sigma_00'].plot() # blue, x location variance
         data_one['sigma_33'].plot() # green, x velocity variance

Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x2e5b55b6ac8>
```

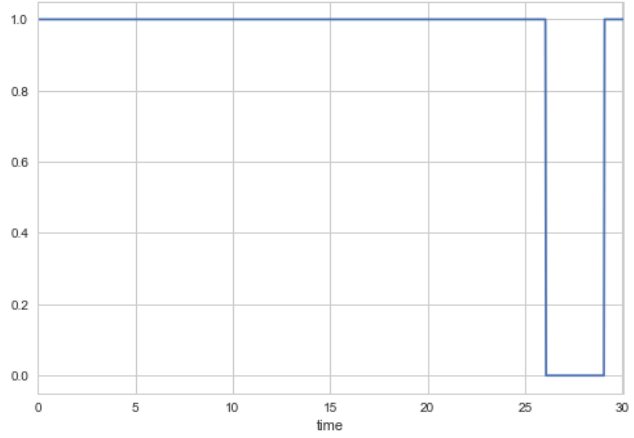


Body Filtering

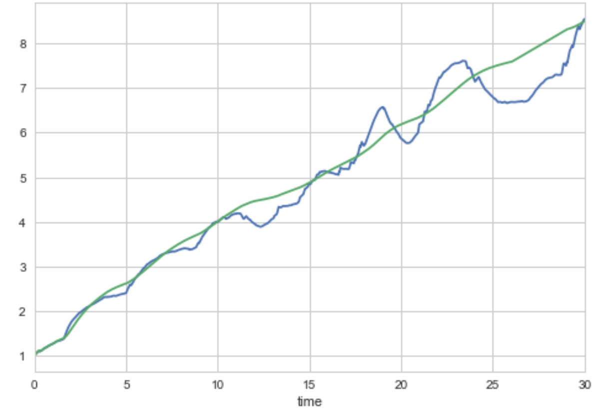
Example 2

Body Filtering

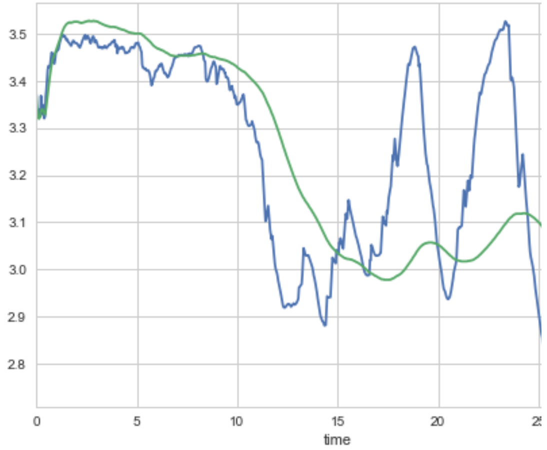
In [5]:
```
data_one['status'].plot()
```
Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x1a52aca5438>



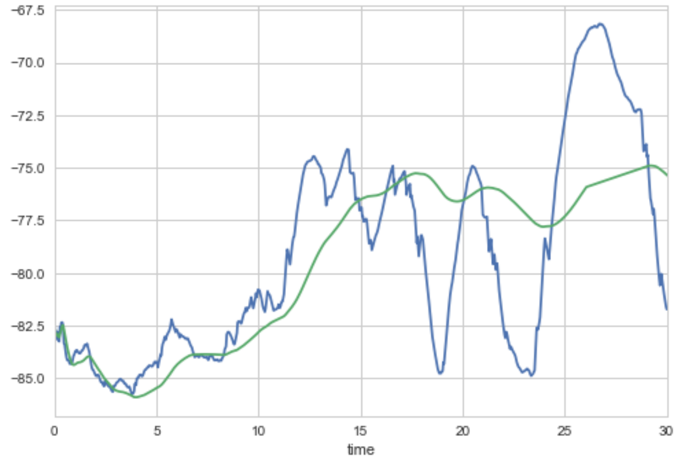
In [6]:
```
data_one['x_pattern'].plot() # blue, measurement
data_one['x'].plot() # green, filtered + predicted
```
Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x1a52bf61470>



In [7]:
```
data_one['y_pattern'].plot() # blue, measurement
data_one['y'].plot() # green, filtered + predicted
```
Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x1a52ad49



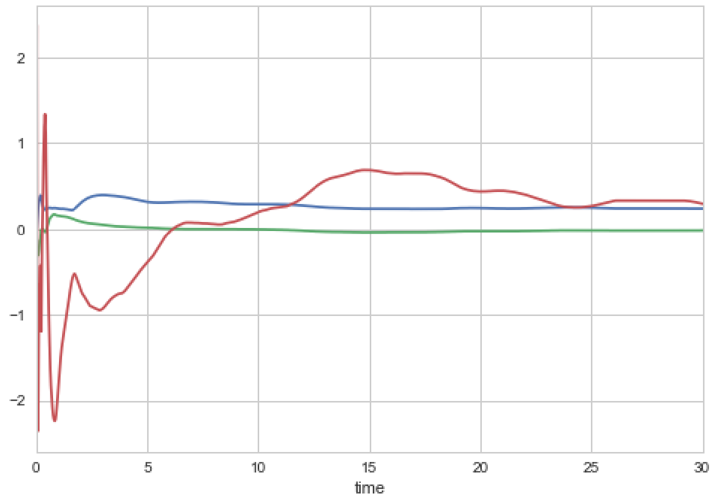
In [8]:
```
data_one['z_pattern'].plot() # blue, measurement
data_one['z'].plot() # green, filtered + predicted
```
Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x1a52c097cf8>



Body Filtering

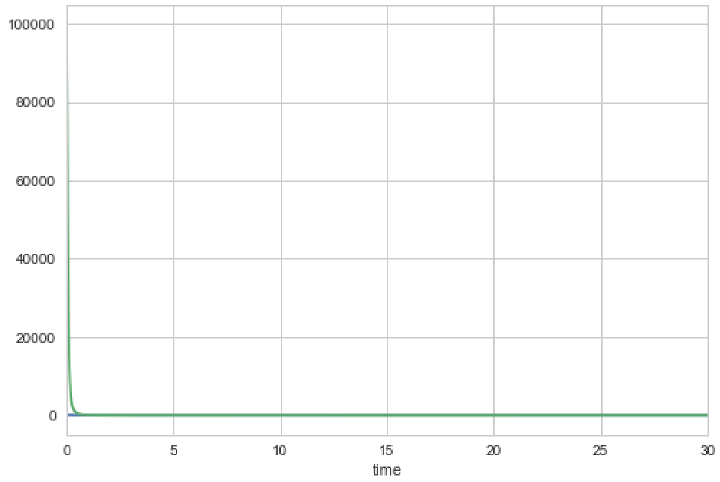
```
In [9]: data_one['vx'].plot() # blue
        data_one['vy'].plot() # green
        data_one['vz'].plot() # red
```

```
Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x1a52708b4a8>
```




```
In [10]: data_one['sigma_00'].plot() # blue, x location variance
         data_one['sigma_33'].plot() # green, x velocity variance
```

```
Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x1a52c184438>
```



Representations for Interpretation

Representation: Video

Object detection network

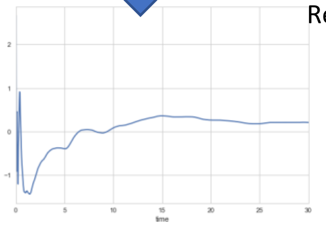
Representation: Pattern

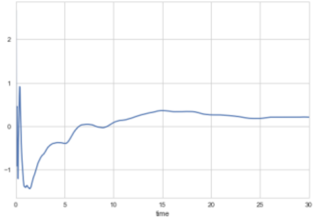
Location and velocity estimation

Representation: Body

Forecast

Representation: Time series





Interpretation Generation

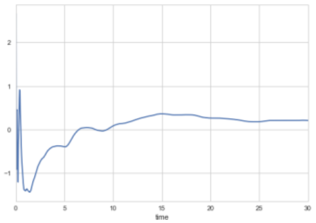
I1 I2 I3 …

Interpretation representations

Language Generation

Representations for Interpretation

Example for interpretation representation: collision detection



Time series forecast for body locations

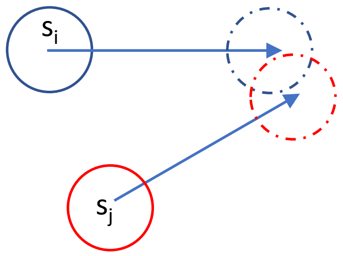
Interpretation Generation

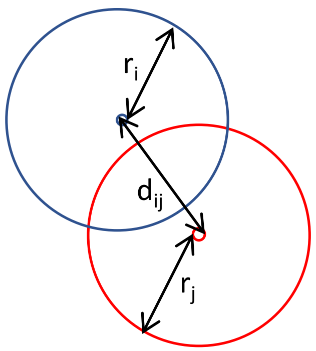
$$\begin{bmatrix} 0 & p_{12} & p_{13} & p_{14} & \dots & p_{1n} \\ p_{21} & 0 & p_{23} & p_{24} & \dots & p_{2n} \\ p_{31} & p_{32} & 0 & p_{34} & \dots & p_{3n} \\ p_{41} & p_{42} & p_{43} & 0 & \dots & p_{4n} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ p_{n1} & p_{n2} & p_{n3} & p_{n4} & \dots & 0 \end{bmatrix}$$

(Symmetric) collision probability matrix

p_{nm} = probability that bodies n and m will collide

Collision Detection





Collision C_{ij} if $d_{ij} < r_i + r_j$

$$\begin{bmatrix} x_i(t) \\ y_i(t) \\ z_i(t) \end{bmatrix} = \begin{bmatrix} x_i(0) \\ y_i(0) \\ z_i(0) \end{bmatrix} + t * \begin{bmatrix} v_{i,x}(0) \\ v_{i,y}(0) \\ v_{i,z}(0) \end{bmatrix}$$

$$d_{ij}(t) = \sqrt{(x(t)_i - x(t)_j)^2 + (y(t)_i - y(t)_j)^2 + (z(t)_i - z(t)_j)^2}$$

Random variable $r = \begin{bmatrix} x_1(0) \\ y_1(0) \\ z_1(0) \\ v_{1,x}(0) \\ v_{1,y}(0) \\ v_{1,z}(0) \\ r_1 \\ \cdots \\ x_n(0) \\ y_n(0) \\ z_n(0) \\ v_{n,x}(0) \\ v_{n,y}(0) \\ v_{n,z}(0) \\ r_n \\ t \end{bmatrix}$ t: uniform distribution on $[0, t_{end}]$

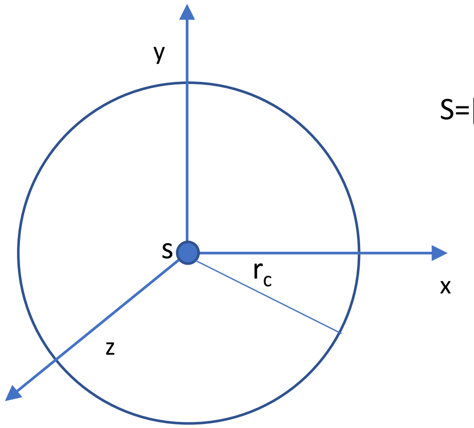
Sampling: $p_{ij} = E\{C_{ij}\} = \sum_{k=1}^{m} \frac{\delta(C_{i,j})}{m}$

Open question:

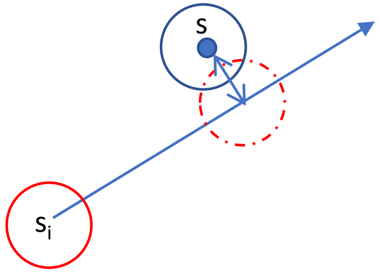
1) Too many dimensions?
2) More efficient sampling with MCMC / Metropolis-Hastings?

Collision Detection

Simpler case: Collision with the observer



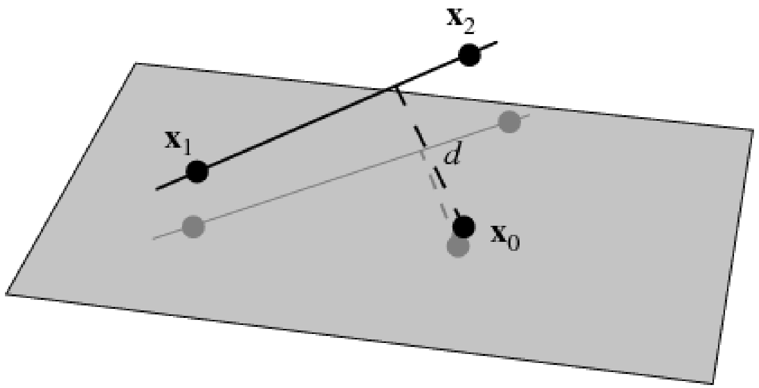
S=[0,0,0,0,0,0]^T , deterministic, r = r[class person]



$$r = \begin{bmatrix} x_i(0) \\ y_i(0) \\ z_i(0) \\ v_{i,x}(0) \\ v_{i,y}(0) \\ v_{i,z}(0) \\ r_i \\ r \end{bmatrix}$$

For each body i, a random vector r is sampled and minimum distance to the observer calculated. If the distance is less than r1+r, collision occurred. The proportion on collisions to all cases is the probability estimate for the body/observer collision.

Collision Detection



$$t = -\frac{(\mathbf{x}_1 - \mathbf{x}_0)\cdot(\mathbf{x}_2 - \mathbf{x}_1)}{|\mathbf{x}_2 - \mathbf{x}_1|^2}$$

$$d = \frac{|(\mathbf{x}_2 - \mathbf{x}_1)\times(\mathbf{x}_1 - \mathbf{x}_0)|}{|\mathbf{x}_2 - \mathbf{x}_1|} = \frac{|(\mathbf{x}_0 - \mathbf{x}_1)\times(\mathbf{x}_0 - \mathbf{x}_2)|}{|\mathbf{x}_2 - \mathbf{x}_1|}$$

In our case:
- x_1=P(0)
- x_2=P(0)+V(0) (loc after one sec)
- x_0=0

- ?

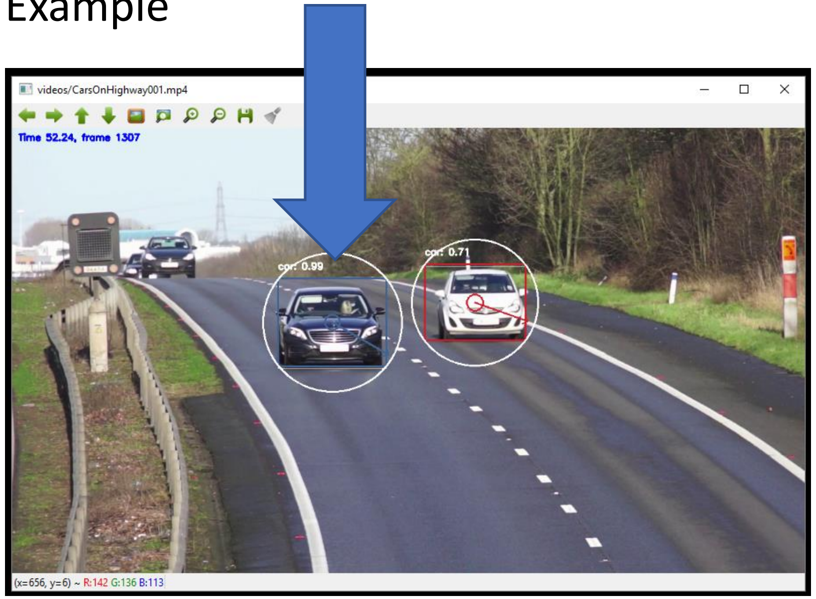
$$t = \frac{(P(0)-0)\cdot(P(0)+V(0)-P(0))}{|P(0)+V(0)-P(0)|^2} = \frac{P(0)\cdot V(0)}{|V(0)|^2}$$

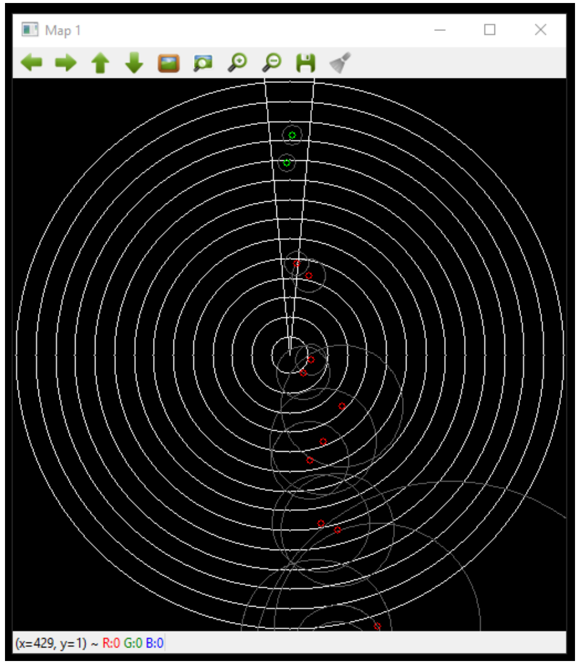
If t<=0, nearest point is P(0)

$$d = |P(0) + t * V(0)|$$

Collision Detection

Example

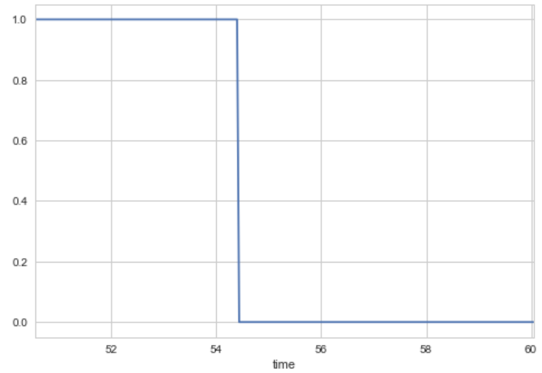




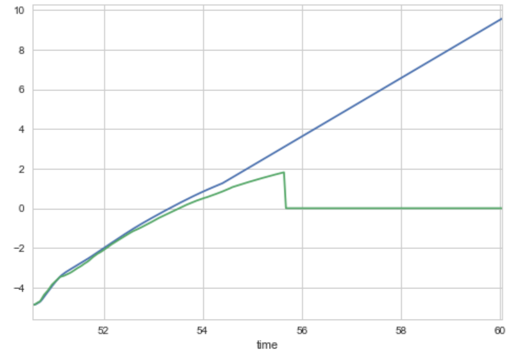
Collision Detection

Example

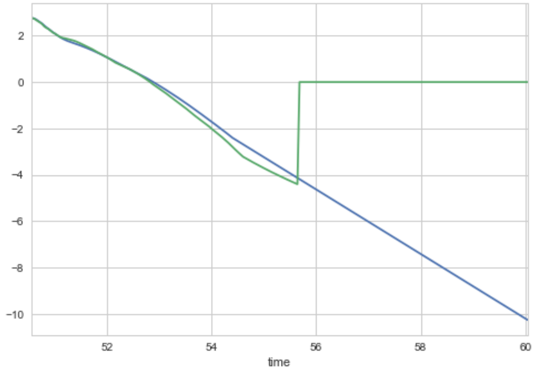
```
In [177]: data_one['status'].plot()
Out[177]: <matplotlib.axes._subplots.AxesSubplot at 0x1b238f06588>
```



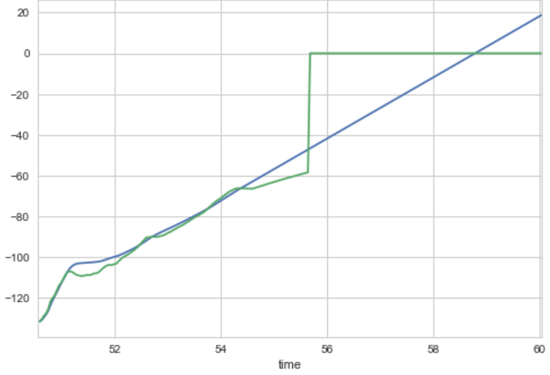

```
In [446]: data_one['x'].plot() # estimated, blue
          data_one['x_pattern'].plot() # measured, green
Out[446]: <matplotlib.axes._subplots.AxesSubplot at 0x1b241357278>
```




```
In [448]: data_one['y'].plot() # estimated, blue
          data_one['y_pattern'].plot() # measured, green
Out[448]: <matplotlib.axes._subplots.AxesSubplot at 0x1b241111898>
```



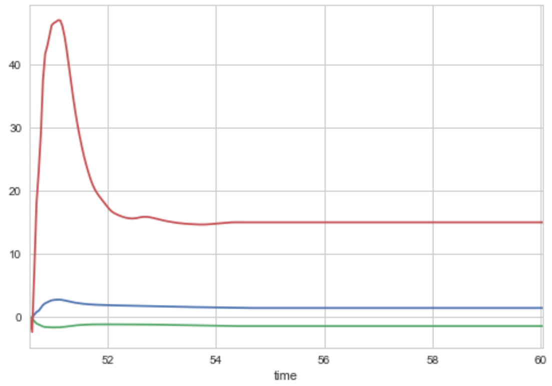

```
In [449]: data_one['z'].plot() # estimated, blue
          data_one['z_pattern'].plot() # measured, green
Out[449]: <matplotlib.axes._subplots.AxesSubplot at 0x1b2390bf0f0>
```



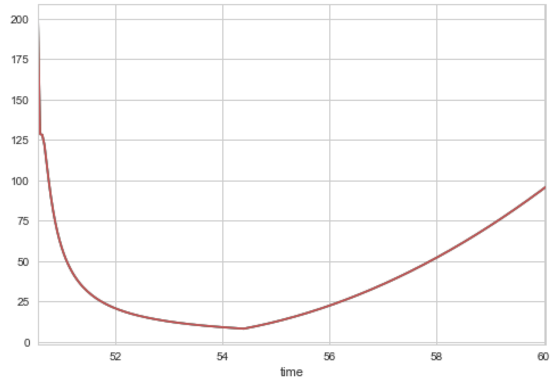
Collision Detection

Example

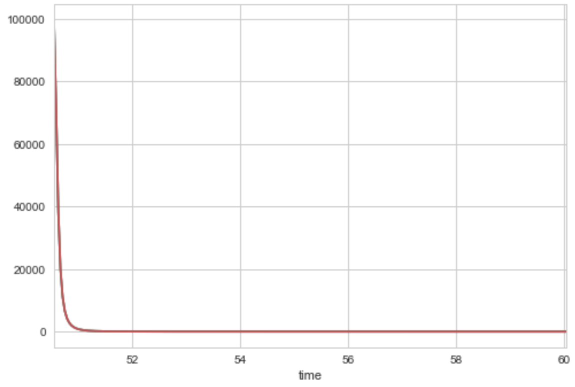
```
In [450]: data_one['vx'].plot() # estimated, blue
          data_one['vy'].plot() # estimated, green
          data_one['vz'].plot() # estimated, red

Out[450]: <matplotlib.axes._subplots.AxesSubplot at 0x1b2391b7c50>
```




```
In [451]: data_one['sigma_00'].plot() # x, estimated, blue
          data_one['sigma_11'].plot() # y, estimated, green
          data_one['sigma_22'].plot() # z, estimated, red

Out[451]: <matplotlib.axes._subplots.AxesSubplot at 0x1b2391a0e10>
```




```
In [452]: data_one['sigma_33'].plot() # vx, estimated, blue
          data_one['sigma_44'].plot() # vy, estimated, green
          data_one['sigma_55'].plot() # vz, estimated, red

Out[452]: <matplotlib.axes._subplots.AxesSubplot at 0x1b2392fb780>
```



Collision Detection

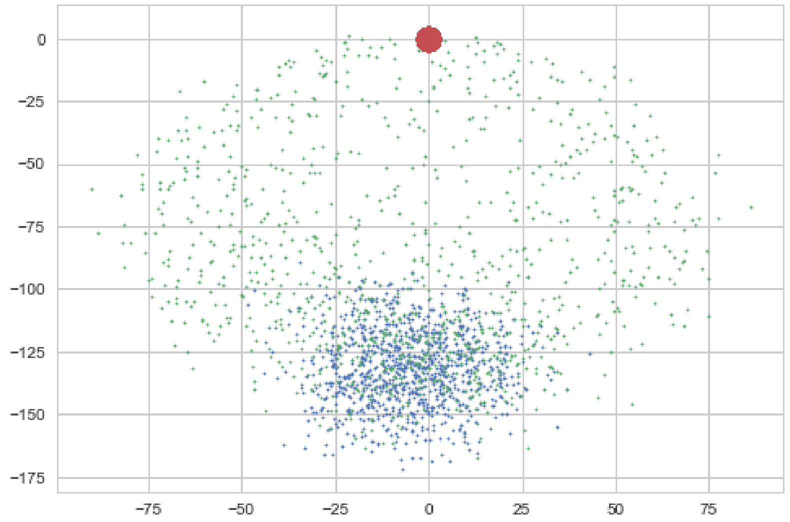
Example

T=50.56 sec

```
In [506]: mu # mean for location and velocity
Out[506]: array([  -4.868,    2.767, -131.242,    0.   ,    0.   ,    0.   ])
```

```
In [508]: sigma # covariance for location and velocity
Out[508]: array([[  1.99601000e+02,   0.00000000e+00,   0.00000000e+00,
                    7.97100000e+00,   0.00000000e+00,   0.00000000e+00],
                 [  0.00000000e+00,   1.99601000e+02,   0.00000000e+00,
                    0.00000000e+00,   7.97100000e+00,   0.00000000e+00],
                 [  0.00000000e+00,   0.00000000e+00,   1.99601000e+02,
                    0.00000000e+00,   0.00000000e+00,   7.97100000e+00],
                 [  7.97100000e+00,   0.00000000e+00,   0.00000000e+00,
                    9.98405740e+04,   0.00000000e+00,   0.00000000e+00],
                 [  0.00000000e+00,   7.97100000e+00,   0.00000000e+00,
                    0.00000000e+00,   9.98405740e+04,   0.00000000e+00],
                 [  0.00000000e+00,   0.00000000e+00,   7.97100000e+00,
                    0.00000000e+00,   0.00000000e+00,   9.98405740e+04]])
```

```
In [537]: plt.scatter(x,z,alpha=1.0,s=2) # blue, start point
          plt.scatter(x_end,z_end,alpha=1.0,s=2) # green, end point
          plt.scatter(xo,zo,alpha=1.0,s=220) # red, observer
Out[537]: <matplotlib.collections.PathCollection at 0x1b243a07a20>
```



P=0.000

Collision Detection

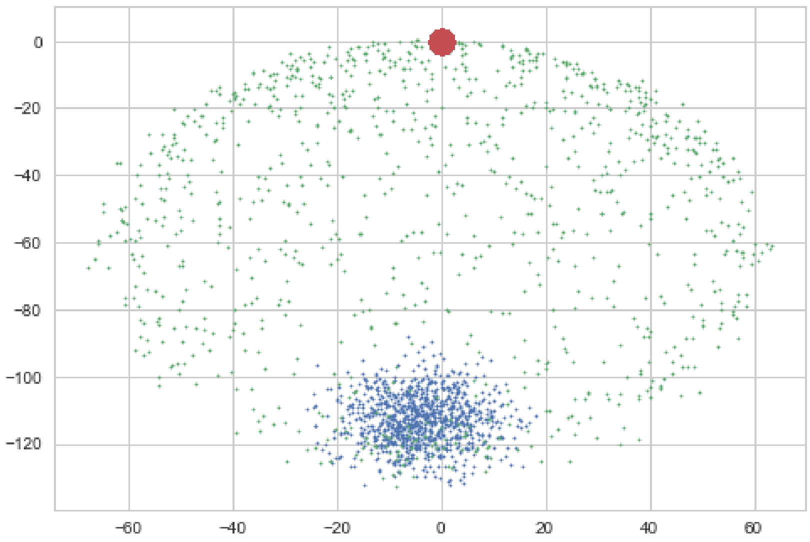
Example

T=51.00 sec

```
In [547]: mu # mean for location and velocity
Out[547]: array([  -3.806,    2.093, -112.909,    2.742,   -1.606,   46.543])
```

```
In [549]: sigma # covariance for location and velocity
Out[549]: array([[  58.597,    0.   ,    0.   ,  190.567,    0.   ,    0.   ],
                 [   0.   ,   58.597,    0.   ,    0.   ,  190.567,    0.   ],
                 [   0.   ,    0.   ,   58.597,    0.   ,    0.   ,  190.567],
                 [ 190.567,    0.   ,    0.   ,  866.044,    0.   ,    0.   ],
                 [   0.   ,  190.567,    0.   ,    0.   ,  866.044,    0.   ],
                 [   0.   ,    0.   ,  190.567,    0.   ,    0.   ,  866.044]])
```

```
In [605]: plt.scatter(x,z,alpha=1.0,s=2) # blue, start point
          plt.scatter(x_end,z_end,alpha=1.0,s=2) # green, end point
          plt.scatter(xo,zo,alpha=1.0,s=220) # red, observer
Out[605]: <matplotlib.collections.PathCollection at 0x1b24597a780>
```



P=0.000

Collision Detection

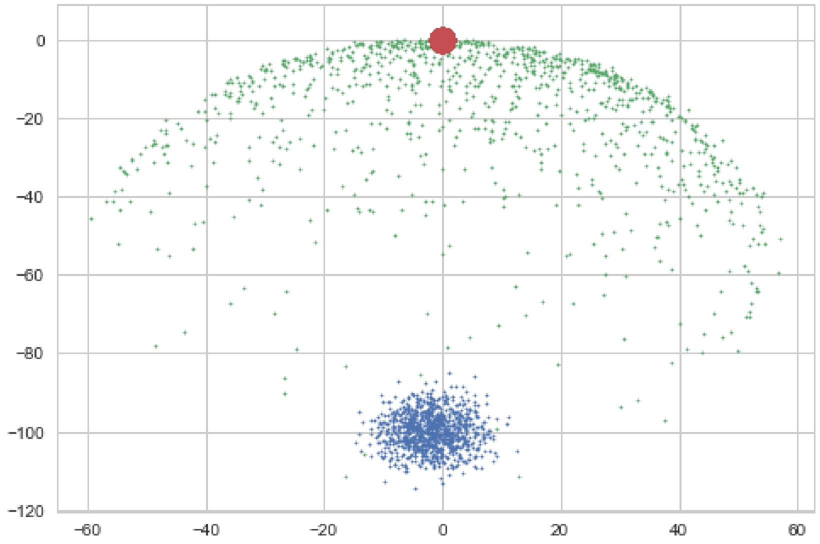
Example

T=52.00 sec

```
In [615]: mu # mean for location and velocity
Out[615]: array([ -2.018,   1.065, -99.876,   1.916,  -1.118,  17.396])
```

```
In [617]: sigma # covariance for location and velocity
Out[617]: array([[ 20.762,   0.   ,   0.   ,  21.328,   0.   ,   0.   ],
                 [  0.   ,  20.762,   0.   ,   0.   ,  21.328,   0.   ],
                 [  0.   ,   0.   ,  20.762,   0.   ,   0.   ,  21.328],
                 [ 21.328,   0.   ,   0.   ,  29.621,   0.   ,   0.   ],
                 [  0.   ,  21.328,   0.   ,   0.   ,  29.621,   0.   ],
                 [  0.   ,   0.   ,  21.328,   0.   ,   0.   ,  29.621]])
```

```
In [639]: plt.scatter(x,z,alpha=1.0,s=2) # blue, start point
          plt.scatter(x_end,z_end,alpha=1.0,s=2) # green, end point
          plt.scatter(xo,zo,alpha=1.0,s=220) # red, observer
Out[639]: <matplotlib.collections.PathCollection at 0x1b245cb0eb8>
```



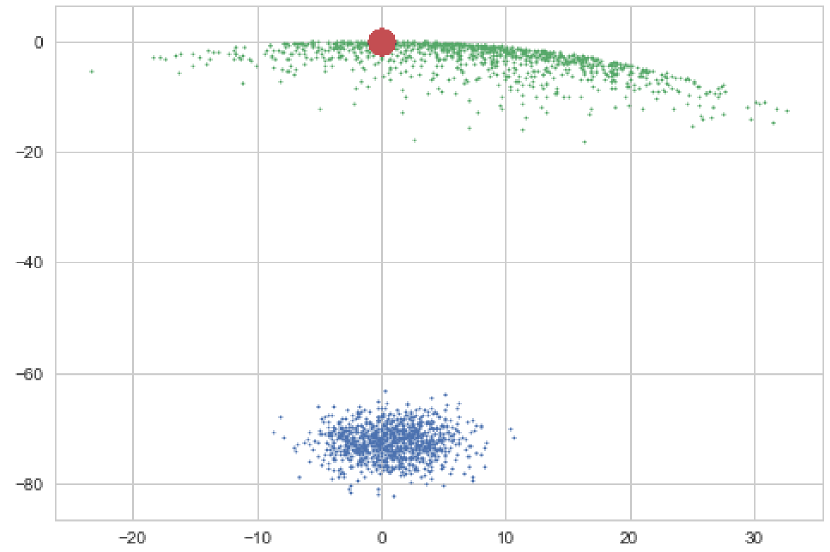
P=0.003

Collision Detection

Example

T=54.00 sec

```
In [661]: mu # mean for location and velocity
Out[661]: array([  0.83 ,  -1.716, -72.372,   1.544,  -1.332,  14.808])

In [663]: sigma # covariance for location and velocity
Out[663]: array([[ 9.038,  0.   ,  0.   ,  3.918,  0.   ,  0.   ],
                 [ 0.   ,  9.038,  0.   ,  0.   ,  3.918,  0.   ],
                 [ 0.   ,  0.   ,  9.038,  0.   ,  0.   ,  3.918],
                 [ 3.918,  0.   ,  0.   ,  2.278,  0.   ,  0.   ],
                 [ 0.   ,  3.918,  0.   ,  0.   ,  2.278,  0.   ],
                 [ 0.   ,  0.   ,  3.918,  0.   ,  0.   ,  2.278]])

In [685]: plt.scatter(x,z,alpha=1.0,s=2) # blue, start point
          plt.scatter(x_end,z_end,alpha=1.0,s=2) # green, end point
          plt.scatter(xo,zo,alpha=1.0,s=220) # red, observer
Out[685]: <matplotlib.collections.PathCollection at 0x1b2455e9f28>
```



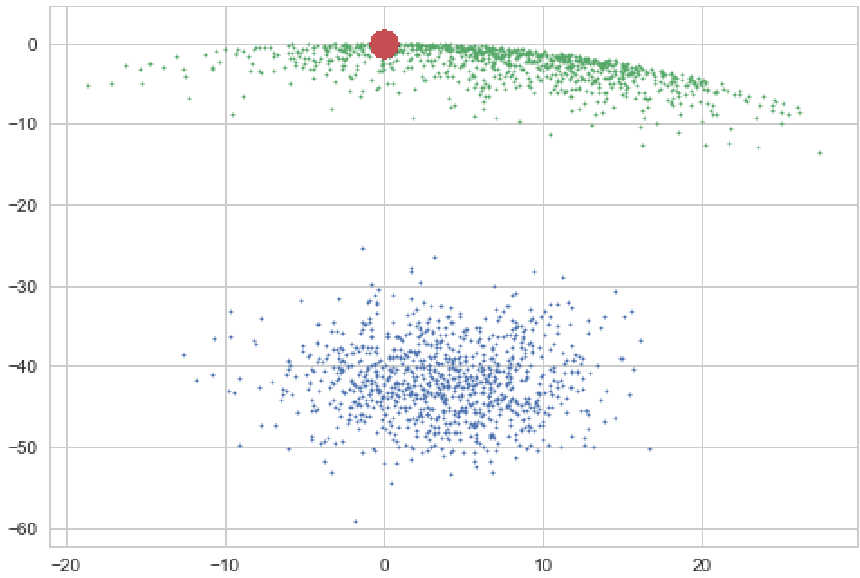
P=0.019

Collision Detection

Example

T=56.00 sec

```
In [695]: mu # mean for location and velocity

Out[695]: array([  3.616,  -4.639, -41.828,   1.473,  -1.393,  15.026])

In [697]: sigma # covariance for location and velocity

Out[697]: array([[ 22.427,   0.   ,   0.   ,   5.785,   0.   ,   0.   ],
                 [  0.   ,  22.427,   0.   ,   0.   ,   5.785,   0.   ],
                 [  0.   ,   0.   ,  22.427,   0.   ,   0.   ,   5.785],
                 [  5.785,   0.   ,   0.   ,   1.644,   0.   ,   0.   ],
                 [  0.   ,   5.785,   0.   ,   0.   ,   1.644,   0.   ],
                 [  0.   ,   0.   ,   5.785,   0.   ,   0.   ,   1.644]])

In [719]: plt.scatter(x,z,alpha=1.0,s=2) # blue, start point
          plt.scatter(x_end,z_end,alpha=1.0,s=2) # green, end point
          plt.scatter(xo,zo,alpha=1.0,s=220) # red, observer

Out[719]: <matplotlib.collections.PathCollection at 0x1b245e5a7f0>
```



P=0.027

Collision Detection

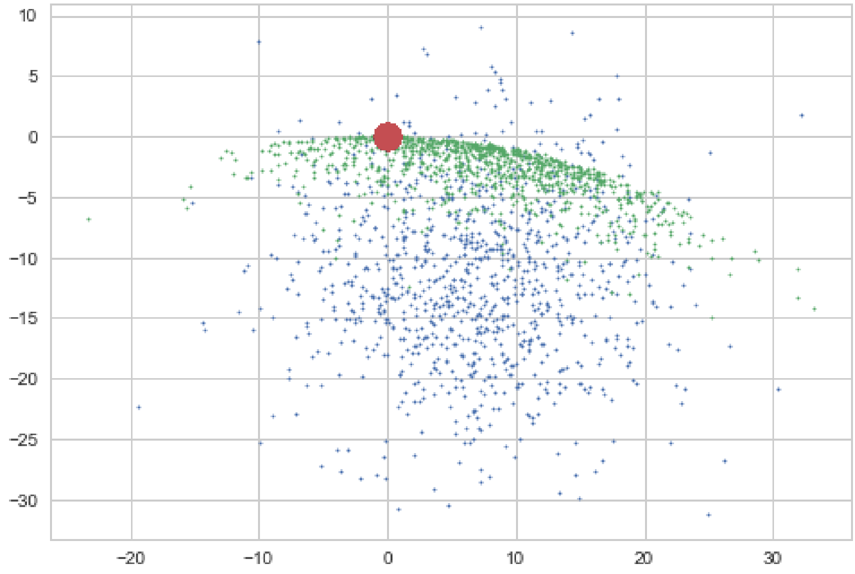
Example

T=58.00 sec

```
In [729]: mu # mean for location and velocity

Out[729]: array([  6.562,  -7.425, -11.777,   1.473,  -1.393,  15.026])
```

```
In [731]: sigma # covariance for location and velocity

Out[731]: array([[ 52.143,   0.   ,   0.   ,   9.073,   0.   ,   0.   ],
                 [  0.   ,  52.143,   0.   ,   0.   ,   9.073,   0.   ],
                 [  0.   ,   0.   ,  52.143,   0.   ,   0.   ,   9.073],
                 [  9.073,   0.   ,   0.   ,   1.644,   0.   ,   0.   ],
                 [  0.   ,   9.073,   0.   ,   0.   ,   1.644,   0.   ],
                 [  0.   ,   0.   ,   9.073,   0.   ,   0.   ,   1.644]])
```

```
In [753]: plt.scatter(x,z,alpha=1.0,s=2) # blue, start point
          plt.scatter(x_end,z_end,alpha=1.0,s=2) # green, end point
          plt.scatter(xo,zo,alpha=1.0,s=220) # red, observer

Out[753]: <matplotlib.collections.PathCollection at 0x1b24716e4a8>
```



P=0.019

Collision Detection

Open questions:

- How to make uncertainty smaller?
- Collision matrix reachable?

Collision Detection

Distance estimation using object radius:

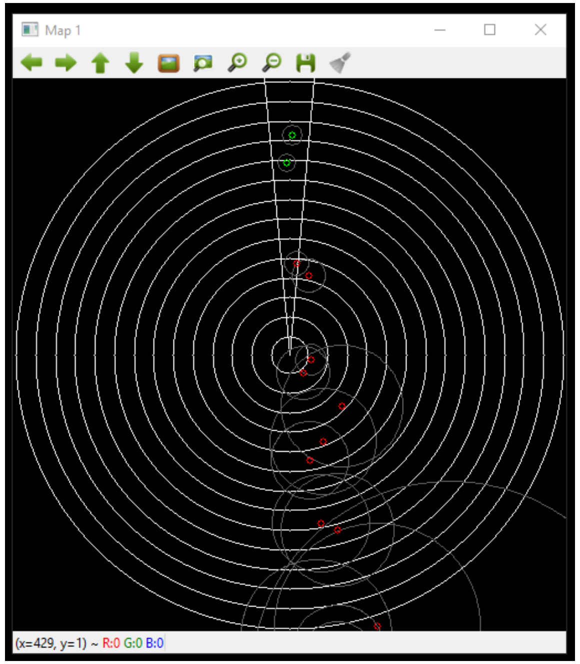
$$t = \frac{d}{\sqrt{{x_c}^2 + {y_c}^2 + {z_c}^2}}$$

$(x_c, y_c, z_c) = (-\frac{s_w}{2} + xp * \frac{s_w}{p_w},\ \ \frac{s_h}{2} - yp * \frac{s_h}{p_h},\ -f)$

$(x_o, y_o, z_o) = t * (x_c, y_c, z_c)$

Prediction

Path chosen - a simpler solution which provides a lot more information



Kalman filter update:

$$\mu_1(k) = A * \mu(k-1)$$

$$\Sigma_1(k) = A * \Sigma(k-1) * A^T + R$$

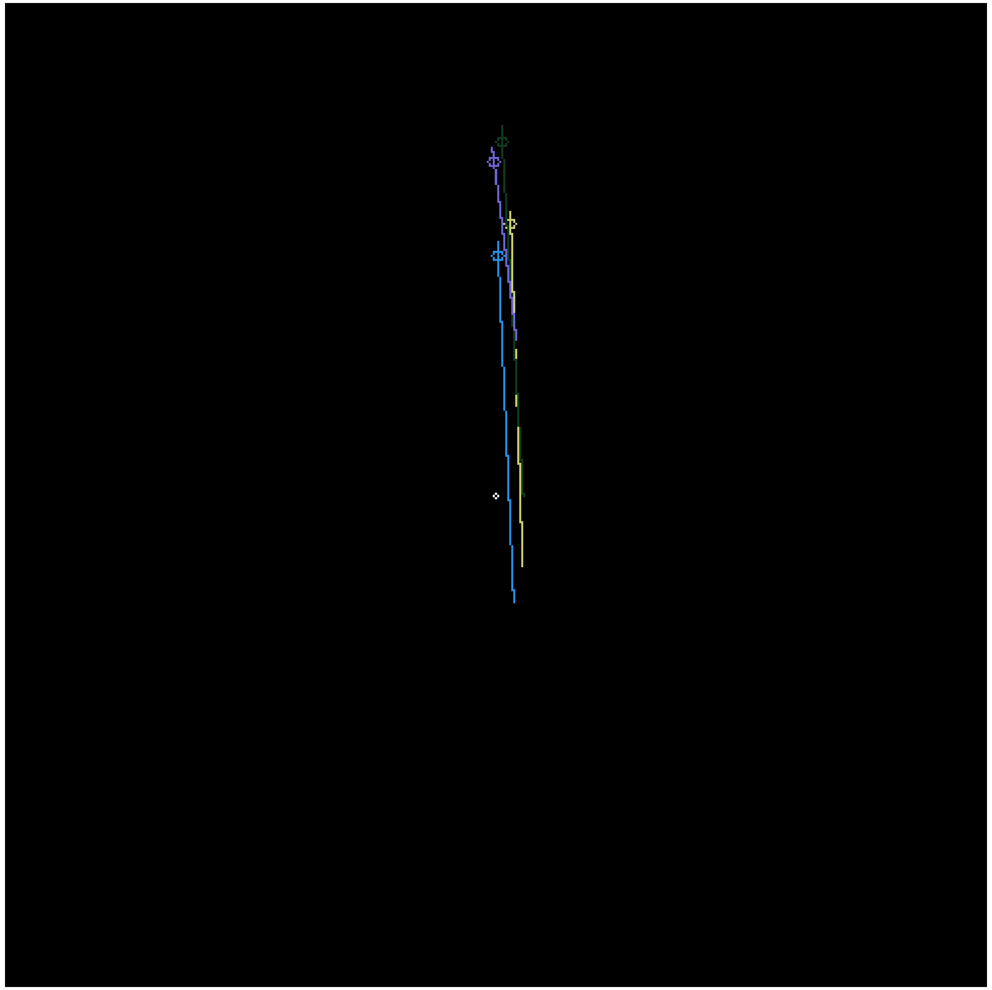
Update is done n times

$$A = \begin{bmatrix} 1 & 0 & 0 & \Delta & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\mu = \begin{bmatrix} x \\ y \\ z \\ v_x \\ v_y \\ v_z \end{bmatrix}$$

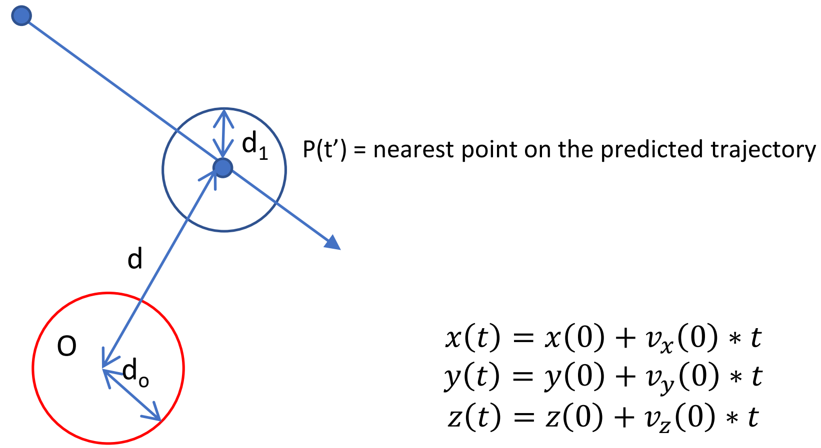
Δ has to be smaller than 1/fps. If fps=25, 1/fps = 0.04 sec. A car driving 120 km/h will proceed 1.33 meters and a collision with an observer might not be detected well enough. A value of Δ = 0.01 corresponds to the movement of 33 cm for an object moving at 120 km/h. This will generate 100 predictions per second. If we want the prediction horizon to be 10 secs, we have 1000 predictions per object. Predicting for every frame will generate fps*1000 ≈ 25 000 predictions per second per object. This is too much, so only current prediction is saved.

Prediction



Collision Detection

Collision with the observer



$$x(t) = x(0) + v_x(0) * t$$
$$y(t) = y(0) + v_y(0) * t$$
$$z(t) = z(0) + v_z(0) * t$$

$$d^2(t) = x(t)^2 + y(t)^2 + z(t)^2$$

$$d^2 = (x(0) + v_x(0) * t)^2 + (y(0) + v_y(0) * t)^2 + (z(0) + v_z(0) * t)^2$$

$$\frac{d(d(t)^2)}{dt} = 2 * (x(0) + v_x(0) * t) * v_x(0) + 2 * \left(y(0) + v_y(0) * t\right) * v_y(0) + 2 * (z(0) + v_z(0) * t) * v_z(0) = 0$$

$$t' = -\frac{x(0) * v_x(0) + y(0) * v_y(0) + z(0) * v_z(0)}{v_x(0)^2 + v_y(0)^2 + v_z(0)^2}$$

Work in Progress

Perception

“The first step in achieving SA is to perceive the status, attributes, and dynamics of relevant elements in the environment. Thus, Level 1 SA, the most basic level of SA, involves the processes of monitoring, cue detection, and simple recognition, which lead to an awareness of multiple situational elements (objects, events, people, systems, environmental factors) and their current states (locations, conditions, modes, actions).”

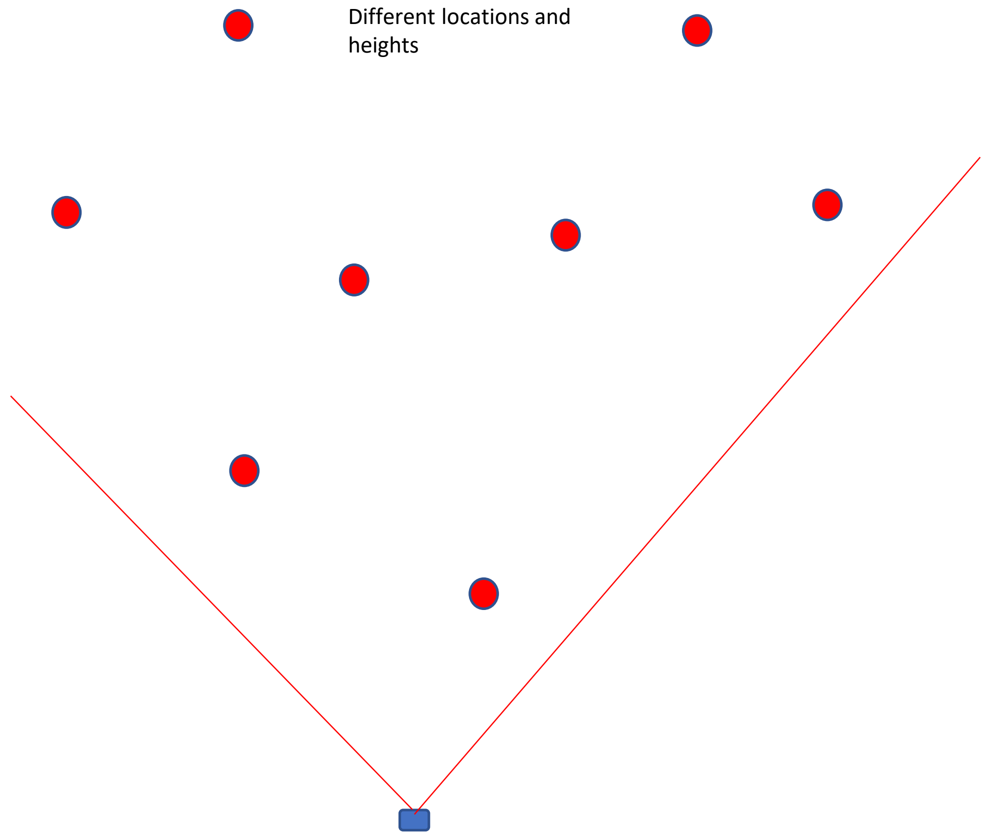
Next Steps

Next steps

- Kalman filter parameter adjustment
- Experiments in wild
- Paper

Experiment In Wild

Experiment 1 in the wild (locations)



Nikon D800E:

s_w = sensor width (m) = 0.0359 m

s_h = sensor height (m) = 0.0240 m

p_w = image width (pixels) = 7360

p_h = image height (pixels) = 4912

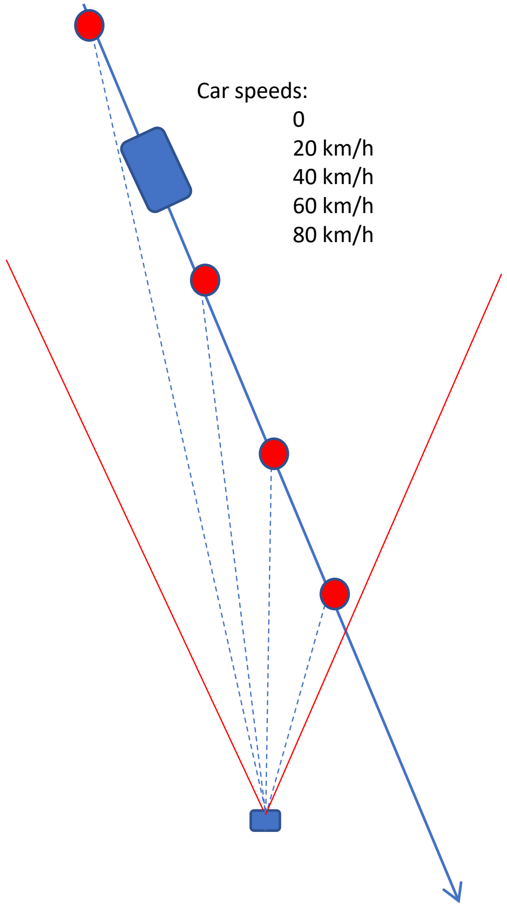
h = object height (m) = 1.5 m

f = focal length (m) = 0.020 m

fov = $2 * \mathrm{atan}(\frac{s_w}{2*f})$ = 83.81 °

Experiment In Wild

Experiment 2 in the wild (moving car)



Distances:
- 10 m
- 20 m
- 30 m
- 40 m
- 50 m
- 60 m
- 70 m
- 80 m
- 90 m
- 100 m

Nikon D800E:
- s_w = sensor width (m) = 0.0359 m
- s_h = sensor height (m) = 0.0240 m
- p_w = image width (pixels) = 7360
- p_h = image height (pixels) = 4912
- h = object height (m) = 1.5 m
- f = focal length (m) = 0.050 m
- fov = $2 * \text{atan}(\frac{s_w}{2*f})$ = 39.49 ^{o}

Paper

Image-based situation awareness: Estimating location and velocity using single camera object detection

Contents:

1. Abstract
2. Introduction
3. Related work
4. Our approach
    1. Definitions
    2. Object identity
    3. Distance estimation
    4. Location and velocity estimation
    5. Movement prediction
5. Experiments
    1. Test setup
    2. Evaluation metric
    3. Results
    4. Other experiments
6. Conclusion

?????

detection, pattern…

Hungarian algorithm, distance metrics, movement prediction

geometry

Kalman filtering

Difference equation, uncertanties

In the wild. See previous slides. More?

Existing datasets? Which?

Paper

- One solution for location estimation and movement prediction for video detected object (nearly) solved

- Work needed:
  - Kalman filter parameter adjustment*
  - Experiments in the wild (see previous slides)
  - Other tests? (using existing (tracking) dataset)

- Where to publish?
  - ECCV 2018 (8-14.9, Munich, deadline 14.3.2018, too soon)
  - CVPR 2019 (6/2019, Long Beach, deadline 11/2018)
  - ICCV 2019 (29.10.-3.11.2019, Seoul, deadline 1/2019)

*Locations and especially velocities take too much time to settle at the moment.

To Be Discussed

To Be Discussed

- Activity recognition?
- Emotion recognition?
- Turning camera, estimation by background movement?

Thank you!

lampola@student.tut.fi
https://github.com/SakariLampola/Thesis