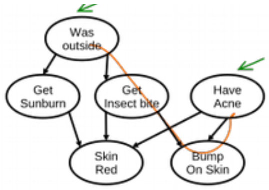
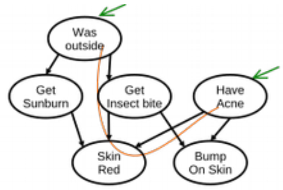
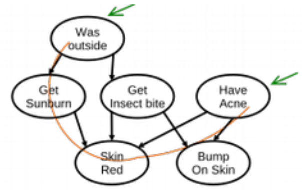
P1.



V triplet (I B A) inactive

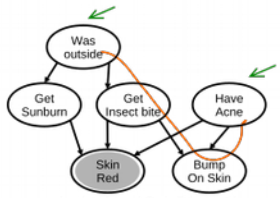


Causal chain (O I R) active
Common effect (I R A) inactive

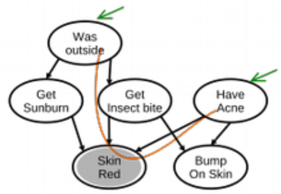


V triplet (S R A) inactive

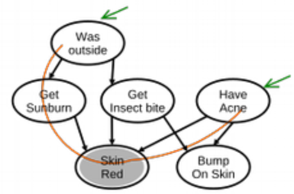
YES. All paths between O and A are inactive; and O and A are guaranteed to be independent.



causal chain (O I R) active
common effect (I R A) inactive

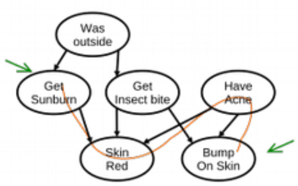


chain (O I A) active
V triplet (I B A) active

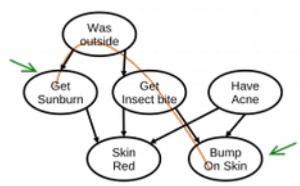


doesn't matter

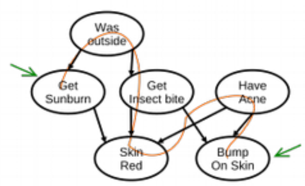
NO. Active path between O and A, independence not guaranteed.



V (I R A) inactive

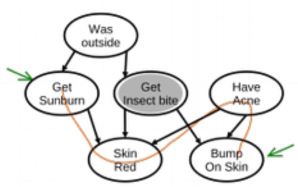


Common cause (S O I) active
Chain (O I B) active

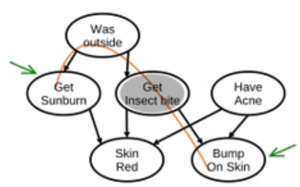


doesn't matter

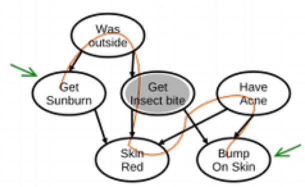
NO. Active path between S and B, independence not guaranteed.



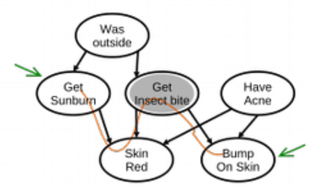
V (I R A) inactive



Common effect (S O I) active
Chain (O I B) inactive

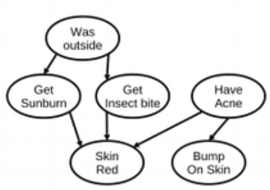


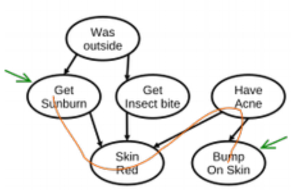
Common effect (S O I) active
Chain (O I R) inactive



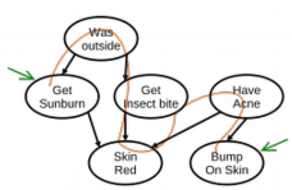
V (S R I) inactive
CCause (R I B) inactive

YES. All paths between S and B inactive. Independence is guaranteed.





V (I R A) inactive



Common effect S O I) active
Chain (O I R) active
V (I R A) inactive

YES. All paths between S and B inactive. Independence is guaranteed.

If we observed R, then we would "activate" the V (common effect) structure I R A. There would then be an active path between S and B, and they would no longer be guaranteed to be independent.

Problem 1 Intuitions.
1. YES, Yes, having acne is independent of going outside. Whether we go outside or not doesn't affect whether we get acne (at least according to this model).
Also, having acne doesn't affect whether we go outside or not (according to this model).

2. NO, If we know whether or not we we have acne, does also knowing whether our skin is red or not impact our estimate of of whether we were outside? If we know we have red skin, and knowing we had acne would "explain away" some of our certainty about being outside or not. Thus, having observed R, O and A are no longer independent.

3. NO, Not independent. The likelihood of us getting sunburned impacts our estimate of being outside, which in turn impacts our estimate of getting an insect bite and potentially having a bump on our skin.

4. YES, Given that we got an insect bite, do we care about whether we have a bump or not, in order to estimate if we are sunburned or not? No! (thus YES, they are independent).

6.

Part 2.1
Update step: see code.
On measurement, multiply Gaussian.
On motion, convolve.

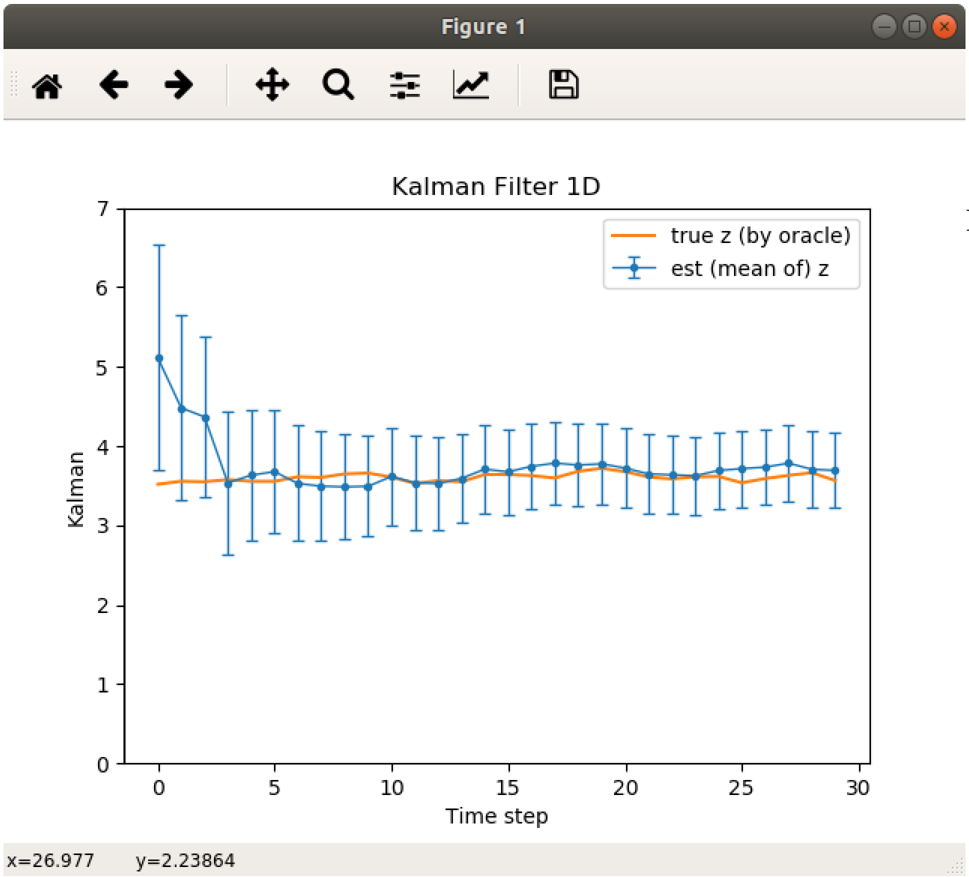


Figure 1
Kalman Filter 1D
true z (by oracle)
est (mean of) z
Kalman
Time step
x=26.977 y=2.23864

Part

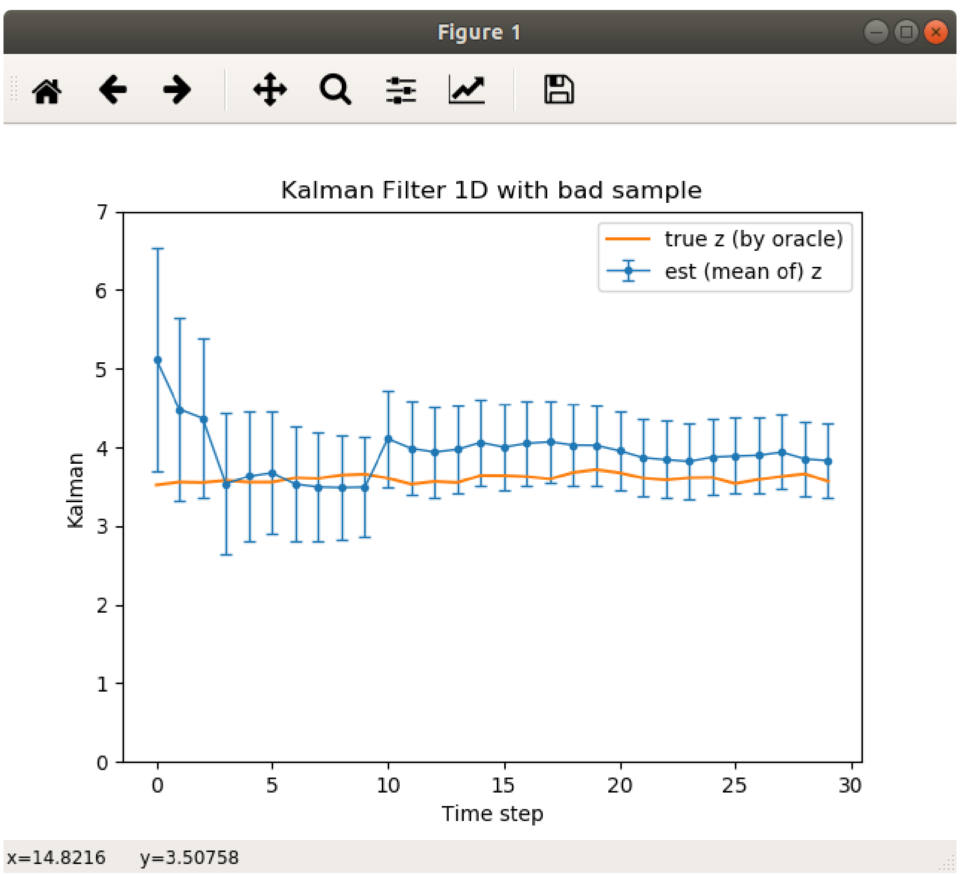


Figure 1
Kalman Filter 1D with bad sample
true z (by oracle)
est (mean of) z
Kalman
Time step
x=14.8216 y=3.50758

Part 3. b.
Yes, Kalman filter catches up to true hidden object.

3. c. Kalman filter mean jumps up but not all the way up to outlier. The standard deviation of our estimate does not actually increase! Continues to monotonically decrease. It starts moving toward the true but after the outlier, it never quite recovers within our window of 30 time samples.

Part 3. d.

```
# Since we think our hidden variable cannot move too far, and we think our measurements are not that
# far off. Thus, when we get a measurement of 3.56 and then a measurement of 10.2, and our
# measurement has settled around 3.5 with only a small variance (0.1), we cannot update our estimate
# of the hidden variable to 10. Instead, we can assume our prior estimate of z is at most (that
# small measurment variance) off, and then the most z can move is on the order of epsilon, and thus
# we update our estimate to be 4.1. Furthermore, since we are fairly certain in our estimates (as
# limited by our initial measurement variance tempered by the mostly consistent samples we've had so
# far), our z estimate will only shift so far on each time step (with a reasonable measurement).
# Thus, at the end of time, our mean still has not recovered to be close to the true z.
```

Part 3.
1.
states = each grid, 1 to 9
actions: going north east south or west
reward(given original state, and action): our expectation of points given our action
If falls off, -1
If lands on 5, -100
If lands on 9, +10.
transition model: likelihood that our policy action will succeed as intended.
2.
Work

			0 = success	-1 = bounced	-100 = fail						+10 = stateA										
Random policy																					
ITERATION 1										FIXED		FIXED	FIXED	FIXED	FIXED						
	p(action)	N	E	S	W					total r	p(reachstate	N s'	E s'	S s'	W s'	vprev(s')	vprev(s')	vprev(s')	vprev(s')		V, 1 step left
1	0.25	fall	fall	OK	fall	-1	-1	0	-1	-0.75	1	1	1	4	1	0	0	0	0		-0.75
2		fall	OK	PIT	fall	-1	0	-100	-1	-25.5		2	3	5	2	0	0	0	0		-25.5
3		fall	fall	OK	OK	-1	-1	0	0	-0.5		3	3	6	2	0	0	0	0		-0.5
4		OK	PIT	OK	fall	0	-100	0	-1	-25.25		1	5	7	4	0	0	0	0		-25.25
5		OK	OK	OK	OK	0	0	0	0	0		2	6	8	4	0	0	0	0		0
6		OK	fall	happy	PIT	0	-1	10	-100	-22.75		3	6	9	5	0	0	0	0		-22.75
7		OK	OK	fall	fall	0	0	-1	-1	-0.5		4	8	7	7	0	0	0	0		-0.5
8		PIT	happy	fall	OK	-100	10	-1	0	-22.75		5	9	8	8	0	0	0	0		-22.75
9		OK	fall	fall	OK	0	-1	-1	0	-0.5		6	9	9	8	0	0	0	0		-0.5
ITERATION 2																					
	pi_axm_pro	N	E	S	W					total r						vprev(N, s')	vprev(E, s')	vprev(S, s')	vprev(W, s')		V, 2 steps left
1	0.25	fall	fall	OK	fall	-1	-1	0	-1	-0.75	1	1	1	4	1	-0.75	-0.75	-25.25	-0.75		-7.625
2		fall	OK	PIT	fall	-1	0	-100	-1	-25.5		2	3	5	2	-25.5	-0.5	0	-25.5		-38.375
3		fall	fall	OK	OK	-1	-1	0	0	-0.5		3	3	6	2	-0.5	-0.5	-22.75	-25.5		-12.8125
4		OK	PIT	OK	fall	0	-100	0	-1	-25.25		1	5	7	4	-0.75	0	-0.5	-25.25		-31.875
5		OK	OK	OK	OK	0	0	0	0	0		2	6	8	4	-25.5	-22.75	-22.75	-25.25		-24.0625
6		OK	fall	happy	PIT	0	-1	10	-100	-22.75		3	6	9	5	-0.5	-22.75	-0.5	0		-28.6875
7		OK	OK	fall	fall	0	0	-1	-1	-0.5		4	8	7	7	-25.25	-22.75	-0.5	-0.5		-12.75
8		PIT	happy	fall	OK	-100	10	-1	0	-22.75		5	9	8	8	0	-0.5	-22.75	-22.75		-34.25
9		OK	fall	fall	OK	0	-1	-1	0	-0.5		6	9	9	8	-22.75	-0.5	-0.5	-22.75		-12.125

Answer

on a grid step 1		
-0.75	-25.5	-0.5
-25.25	0	-22.75
-0.5	-22.75	-0.5
on a grid step 2		
-7.625	-38.375	-12.8125
-31.875	-24.0625	-28.6875
-12.75	-34.25	-12.125

Optimal action					
	sanity check	**V max**			
S	0		▼	▶	▼
E	0		▲	▲	▼
S	0		▲	▶	▲
N	0				
N	0				
S	10				
N	0				
E	10				
N	0				

Work
Ans

Optimal acti	**sanity check**	**V max**			
S	0		▼	▶	▼
E	0		▼	▶	▼
S	10		▲	▶	▲
S	0				
E	10				
S	10				
N	0				
E	10				
N	10				

Part 3 4.
t=1

expected R	
-0.2	Time = 1
-10.1	
-0.1	
-10.1	
0	
-2.1	
-0.1	
-2.1	
-0.1	

did not get to t=2

the policy is no longer optimal.

Part 4.
Worked with:
Eric
Philip
Will

Materials from:
CS188 Berkeley
Udacity Intro to Robotics CS373

Hours:
20-30??

name:
nao ouyang