

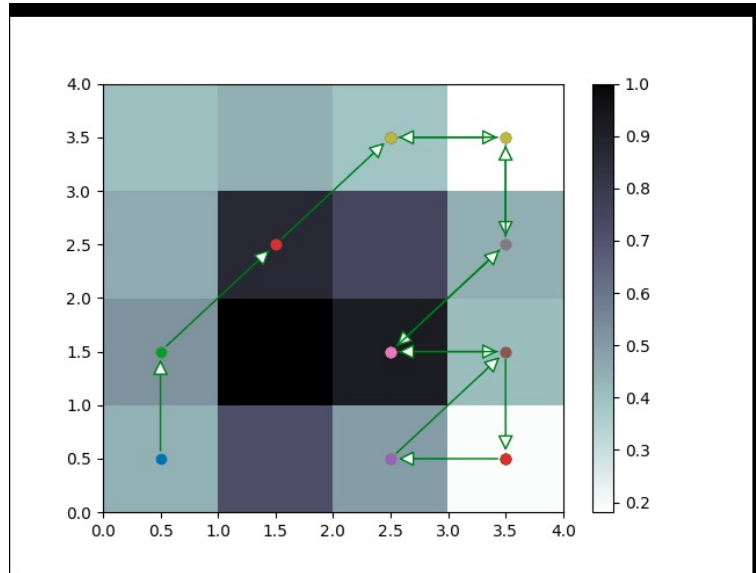
AE/VAE-SOM

Goal for the project:

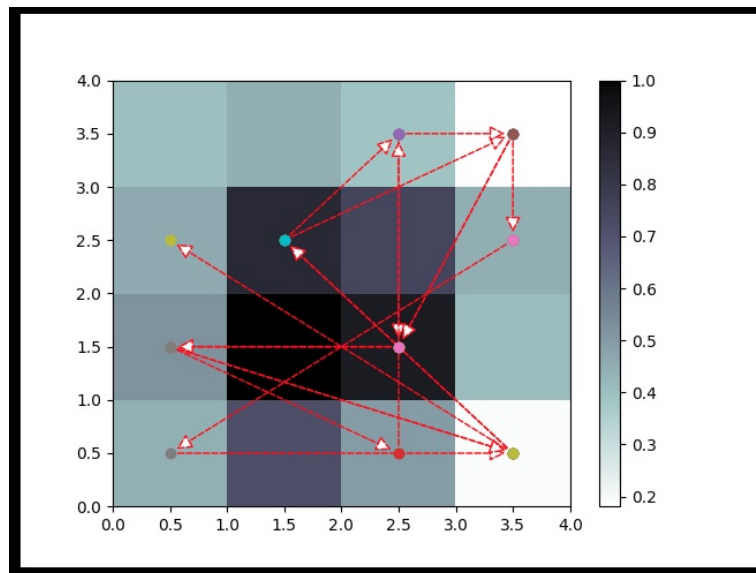
1. Latent space exploration of SOM.
2. Representation learning of AE/VAE/GAN.
3. Anomaly detection for time-series data.
 - o 1) Spatial anomaly detection.
 - o 2) Temporal anomaly detection.
 - o 3) Generalization and robustness of the Algorithms.
4. Quantization of uncertainty.
 - o 1) Spatial uncertainty.
 - o 2) Temporal uncertainty.

Updated May 27th:

- Common Trajectory:



- Faulty Trajectory:



To do list after May 27th update:

1. Investigate correlation between the common input vs. faulty input
2. How to process the bidirectional arrow in the Common trajectory?
3. How to down sample the z_e ?
4. Markov Model

Updated June 4th:

- Fixed up the Markov Chain. Need to be validated.
 - o Note: The Markov Chain is not the only method to optimize the temporal model.
- Set up a new block for spatial anomaly detection.
 - o $P_{anomaly}(v) = 1 - \exp(-(error_q v / \sigma))(1)$.
 - o v refers to input data.
 - o σ refers to $\frac{1}{2} \cdot ||w_{bmu}(v) - w'_{bmu}(v)||$
 - o $error_q v$ refers to $||v - bmu(u_i)||$
- σ means the divergence of the data. sigma is larger, the results are more dispersed. σ should be around $0.5 \rightarrow 1.5$. Learning rate should be around $0.5 \rightarrow 2.5$. The map size should not more than (10, 10).
- The detail about hyper parameters can be found here [A simple demo for Hyper parameters](#)

- An example:
- Loss

To do list after June 4th's update

1. Fidy the source code:
2. Change the dataset.
 - *Socketsense*
 - *Itrust*
3. Add a new block for anomaly detection in Spatial space. It needs to test more to avoid FP.
4. The hyper-parameters needs to be clarify in order to get a better results in SOM.
5. Temporal anomaly detection.
 - Investigation in Markov Chain
 - Investigation in Affinity Matrix. (Continue to abstract for the SOM neuron).
6. Confirm the Spatial anomaly detection and V&V results.

Updated June 5th

1. The mapsize should be calibrated with the σ . In other words, when map size is larger, the sigma should be larger. **Question: How we should interpret these two hyper parameters?**
2. The Sin function has been replaced by SocketSense.
3. Function update:
 - Add a new block to check the FP.
 - Add a new block to generate the affinity(similarity) matrix, which could be treated as *Truth table*.

To do list after June 5th's update

1. Normalization the Affinity matrix, which should either indicate the probability or similarity.
2. Continue to work on the temporal anomaly detection.

Updated June 8th

1. Get the Affinity probability of each *Path state*.
2. Visualization each Affinity Probability according to
 - $P_{affinity} = \exp(-distance(w_i, w_j)/\delta)(2)$
 w_i refers to the path state, w_j refer to the other state
 I set a threshold δ , to select the affinity. When $P_{affinity} > \delta$, we treat w_j as *affinity state*.
3. Map the input to SOM.
 - For example, in our case, we have four pressures, these four pressure's sum will map with the Som. When the Pressure is larger, the color is deeper.
4. Overview results.
 - Temporal path-state trajectory.
 - Visualization of affinity and path states.

To do list after June 8th's update

1. Reschematic Markov Chain:
 - The Markov Chain should save as a table (dataframe) such as following:

	S1	S2	S3
S1	\times	P_{12}	P_{13}
S2	P_{21}	\times	P_{23}
S3	P_{31}	P_{32}	\times

2. Add text (probability) in the temporal trajectory figures.
3. Write a Problog program for the figures.

Discussion

1. How can we prove that *Formula (2)* is reliable?
 - Usually, we should use $(w_i - w_j)^2$ to compute the affinity matrix. But in this case, if we use square, the amount of affinity state will increase a lot. Is *Formula (2)* reasonable?
 - How should we understand δ ?
2. How can we improve/calibrate the method used to map the input data to SOM?
3. Validate our data.....(This may meet a lot of problems)

Updated June 12h

1. The sampling problem can be checked from the following link (the classical methods):
 - [Engineering statistics handbook](#).
2. Fix up the datatype of Markov Transition Matrix.
3. Fix up some bugs.

Discussion

1. How can we understand **Average Sample Number (ASN)**?
How we understand the $\beta = 0.029$ and which value should be p_2 in [Double Sampling Plan](#)?
2. In the [Double Sampling Plan](#), they should define the P_1 .
For example, As I understand, $P_1 = 1 - \alpha + \beta$, although α and β belong to different threshold $< n_1, c_1 >$ and $< n_2, c_2 >$.
3. Should Markov Chain have a sample step(frequency) as sampling data? Otherwise, the tranistion probability would equal to 0 if we use the upsampling states, which shows as below:

Updated June 15h

1. Add a flowgraph to illustrate the workbench.

Note: the sampling problem has not added into the flowgraph. It is a critical problem we should consider now.

Discussion

- 1. How should we sample the data?
 - 2. How can we merge the slide windows in our code?
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Updated June 22rd

- 1. Fulfill the similarity and temporal graph to show the dependency.
!

- 2. Some summary for the potential publication.

- 1) What's the purpose of SOM used in latent space?

SOM can be understood as the measurement of latent space's Euclidean distance.

- 2) Spatial modeling

$$ELBO : \mathbb{E}_{PD(x)} [\log p_{\theta}(x)] \geq \mathbb{E}_{PD(x)} [\mathbb{E}_{q_{\phi}(z|x)} [\log p_{\theta}(x|z)] - \mathbb{KL}(q_{\phi}(z|x)||p(z))]$$

$$Threshold : H_0 \text{ and } H_1$$

$$Similarity : g(z_i, z_j) = \exp(-distance(w_i, w_j))/\delta$$

$$Spatialanaomly : g(z_i, z_j) \text{ compare to } H_0 \text{ and } H_1$$

$$VAE : \mathcal{L}_{vae} = \mathbb{E}_{PD(x)} [\mathbb{E}_{q_{\phi}(z|x)} [\log p_{\theta}(x|z)] - \mathbb{KL}(q_{\phi}(z|x)||p(z))]$$

$$Loss \text{ for the observation and latent space} : \mathcal{L}_{vae-som}(\phi, \theta, x_i, x_j) = \mathcal{L}_{vae}(\phi, \theta, x_i, x_j) + g(z_i, z_j)$$

- 3) Temporal modeling

How we get the threshold of temporal modeling?

- 3. Add a function for sliding window.