Wildfire Segmentation from remotely sensed data using quantum-compatible conditional Vector Quantized-Variational Autoencoders

TU3.R10.4. Quantum Machine Learning algorithms for EO

IGARSS 2024

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Presented by: Ata Akbari Asanjan[2,3]
Co-authors: Lucas Brady[1], Nishchay Suri[1], Zoe Gonzalez Izquierdo[1] , P. Aaron Lott[1,3], Shon Grabbe[1], Eleanor Rieffel[1]

(1): Quantum Artificial Intelligence Laboratory (QuAIL), NASA Ames Research Center
(2): Data Science Group (DSG), NASA Ames Research Center
(3): Universities Space Research Association

Importance of Wildfire Observation

- Wildfire occurrences have been increasing for the past decades, leaving devastating traces across the globe.
  - *Example: 2018 wildfires in California: $148.5 Bn[1]*
- Proper resource management is crucial in the fight against wildfires.
- Accurate detection is the first step in proper wildfire management.
- Proper machine learning techniques can help discover remote sensing-based information that can help us better characterize wildfires.

Credit: USGS

[1] Wang et al., "Economic footprint of California wildfires in 2018," Nature Sustainability, 4, 252-260 (2021)

Credit: Gaurdian

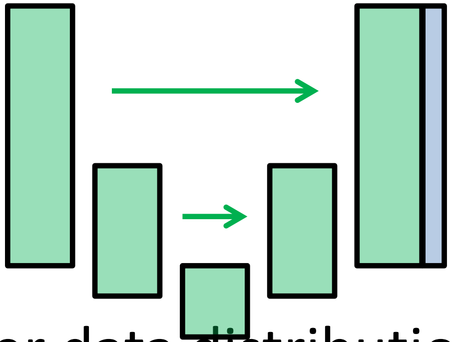
Dataset

- We used the observations of NASA’s Terra and Aqua MODIS for
  - Land/Cloud/Aerosols Boundaries
  - Land/Cloud/Aerosols Properties

- We collected the wildfire mask data from thermal anomalies/active fire product of NASA’s Visible Infrared Imaging Radiometer Suite (VIIRS) onboard the Suomi National Polar-Orbiting Partnership (Suomi NPP).
- We collected 10,000 wildfire samples (with overlapping incidents) over CONUS for the time range of 2018-2020.
- Normalized Difference Vegitation Index (NDVI) is also calculated and included as proxy of vegetation health.
- We included a deviation from mean NDVI accounting for sudden shifts in NDVI in a region.

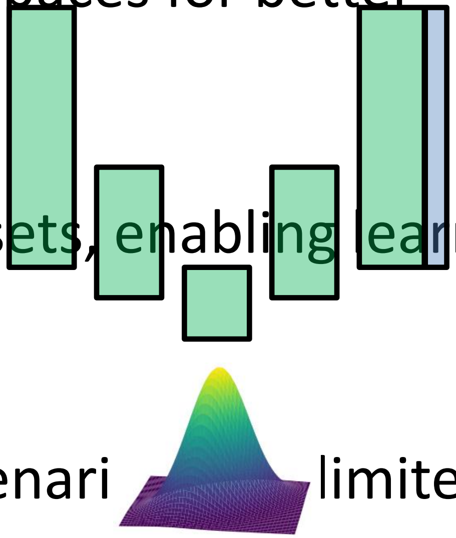
Background – Model Choice

U-NET to VAE Transition



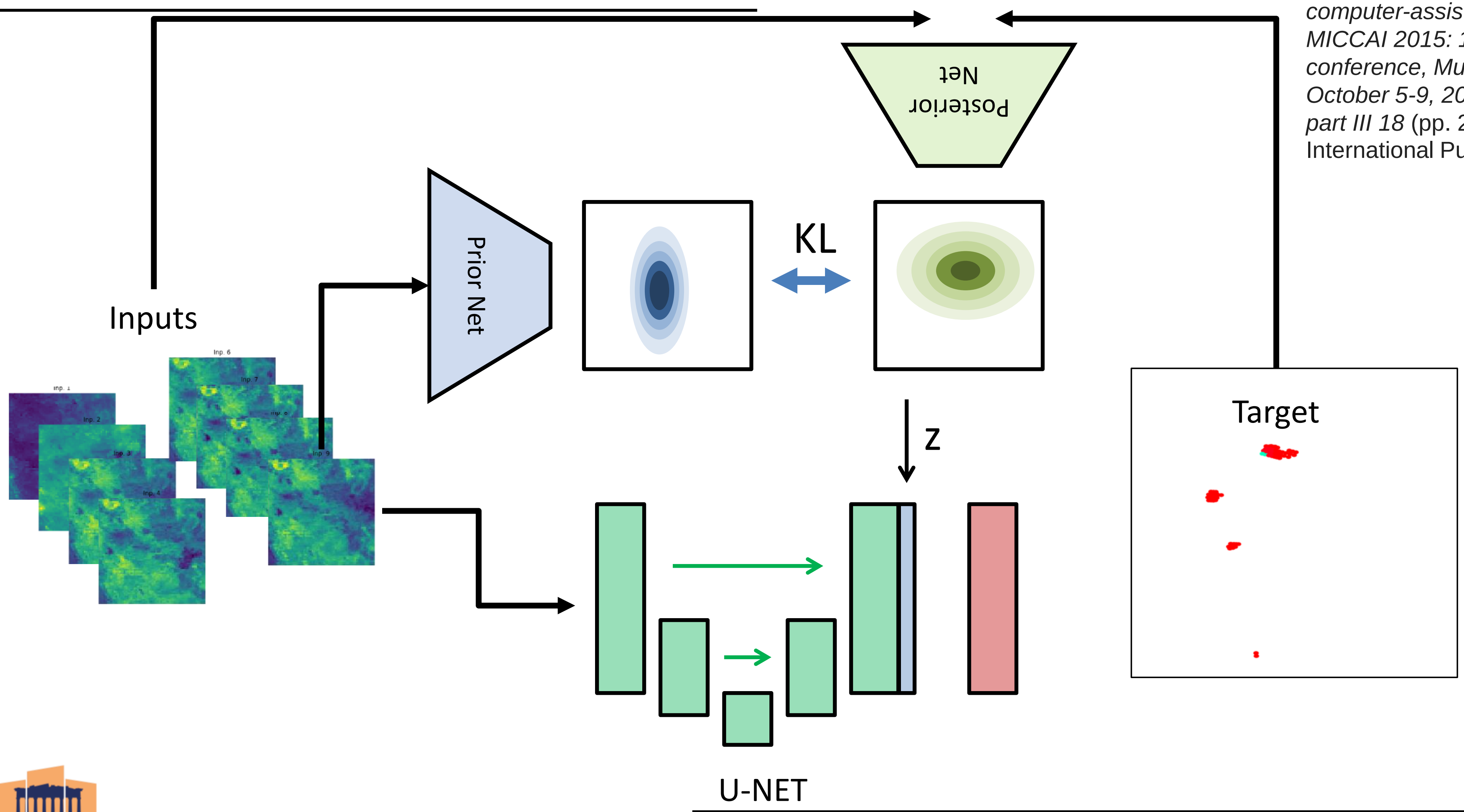
U-NET

- **Goal Shift**: From pixel-perfect segmentation to understanding broader data distributions.
- **Enhanced Generalization**: VAE models input into continuous latent spaces for better generalization across tasks.
- **Unsupervised Learning**: Reduces dependence on large labeled datasets, enabling learning from unlabeled data.
- **Data Augmentation**: VAEs generate new data instances, aiding in scenari limited data.



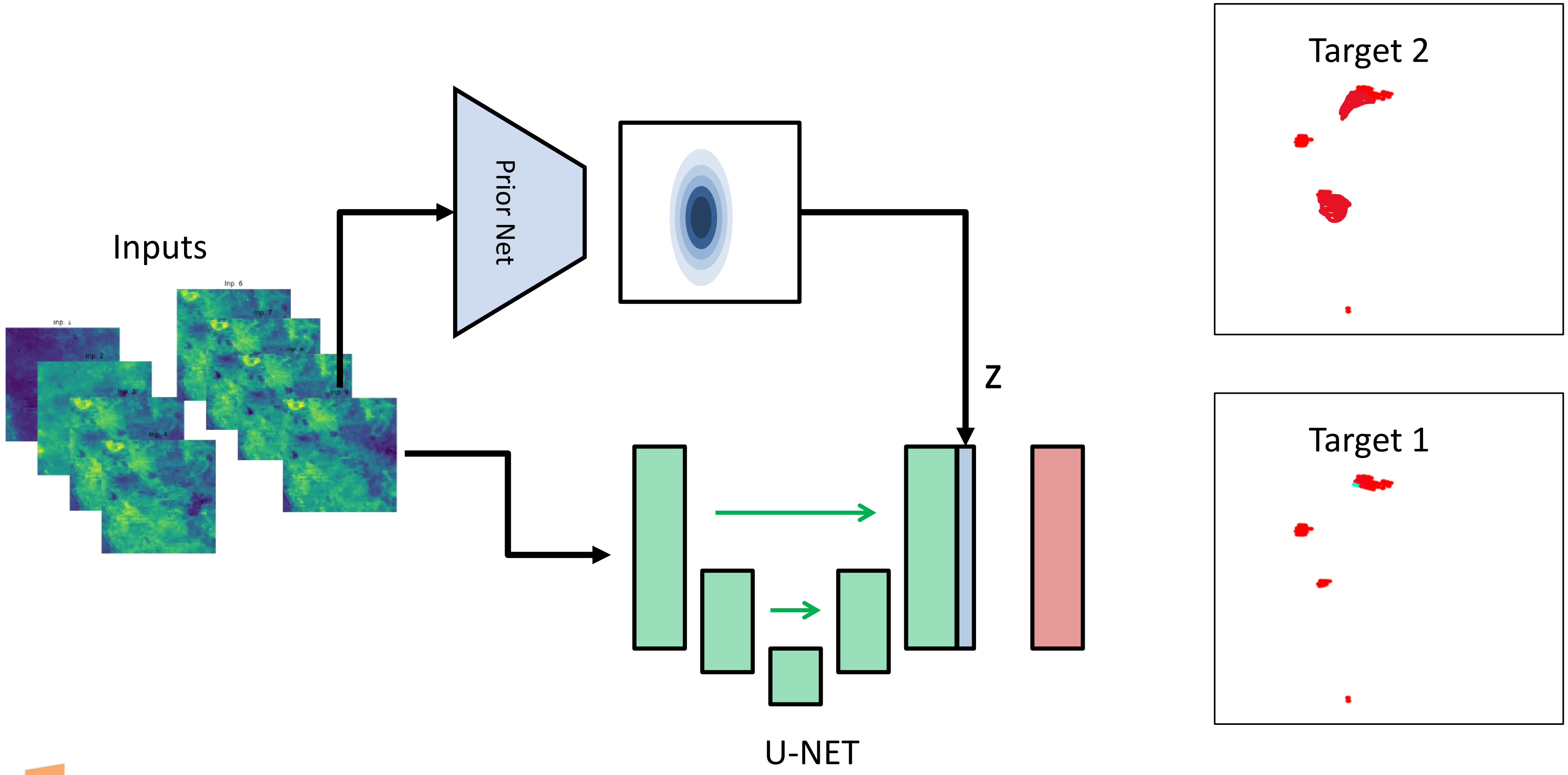
VAE

Probabilistic U-NET – Training Mode

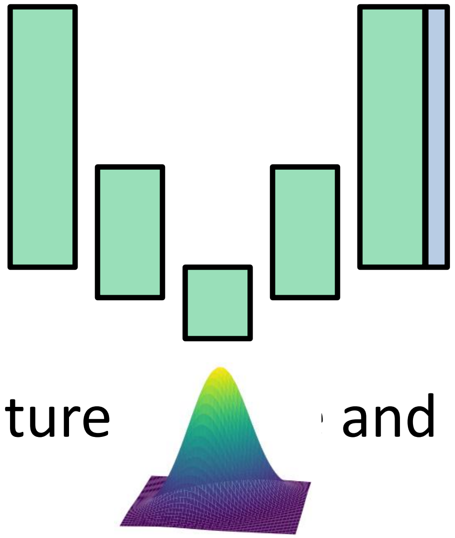


Ronneberger, O., Fischer, P., & Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. In *Medical image computing and computer-assisted intervention–MICCAI 2015: 18th international conference, Munich, Germany, October 5-9, 2015, proceedings, part III 18* (pp. 234-241). Springer International Publishing.

Probabilistic U-NET – Inference Mode

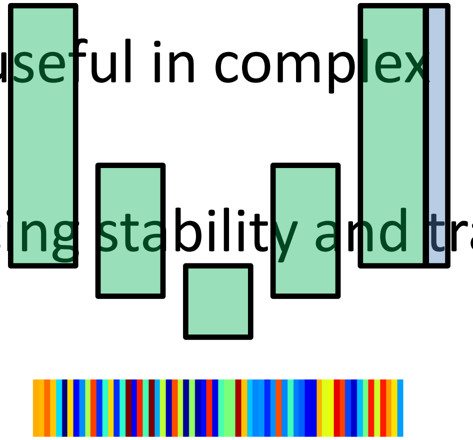


VAE to Vector Quantized (VQ)-VAE Transition



VAE

- **Discrete Latency**: VQ-VAE uses discrete latent spaces for better feature and robustness.
- **Complex Feature Handling**: Improved maintenance of high-quality, detailed features in reconstructions.
- **Hierarchical Representation**: Allows multi-scale data abstraction, useful in complex segmentation tasks.
- **Computational Efficiency**: Simplifies the sampling process, enhancing stability and training efficiency.



VQ-VAE

Vector Quantized Variational Autoencoder (VQ-VAE)

Reconstruction Loss
+
Vector Quantization Loss
+
Commitment Loss

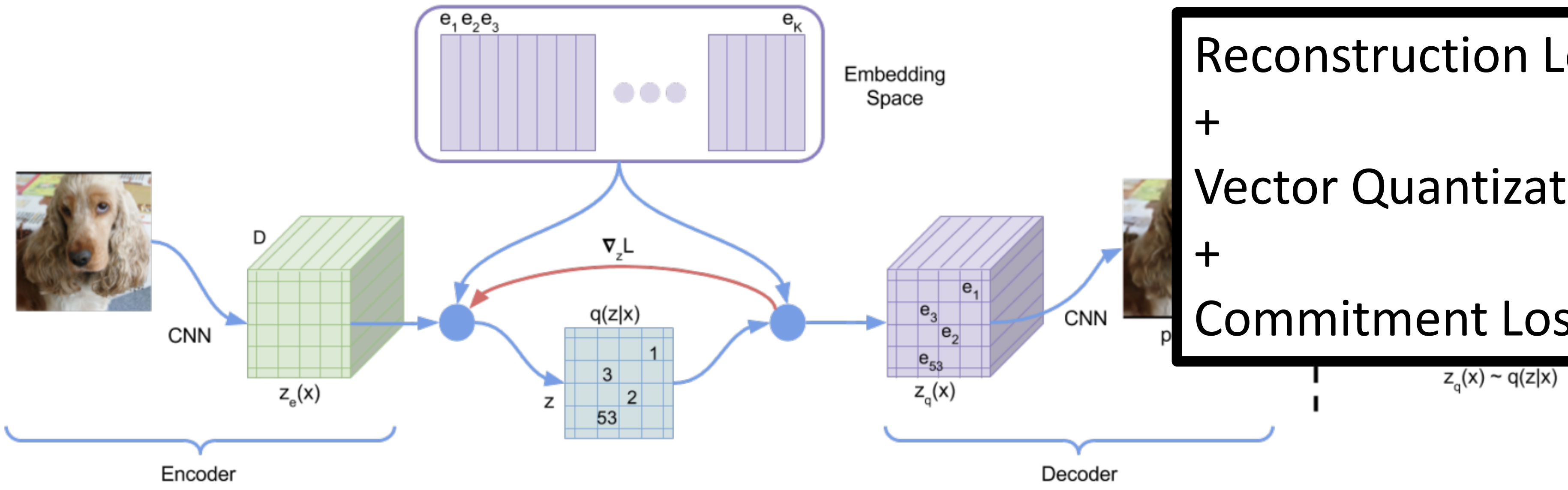
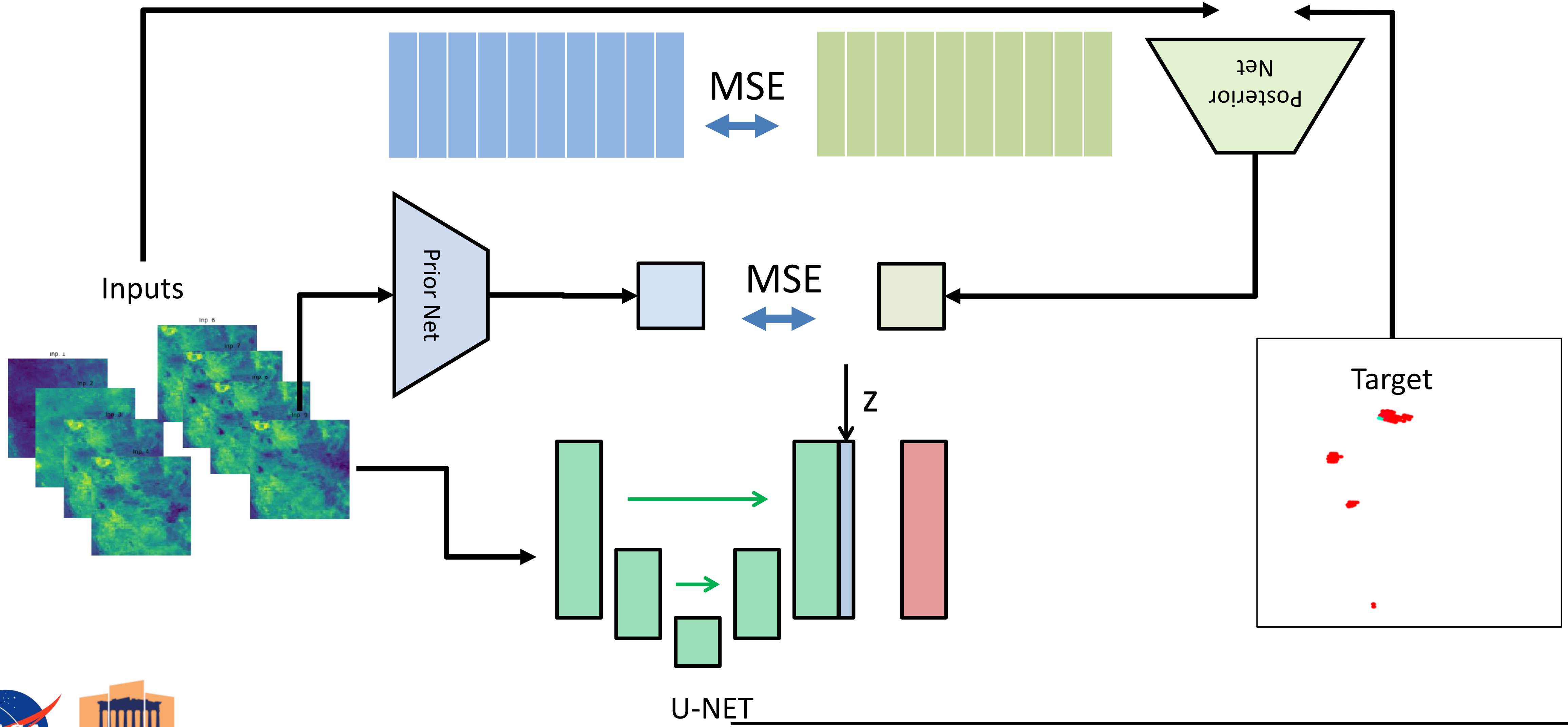


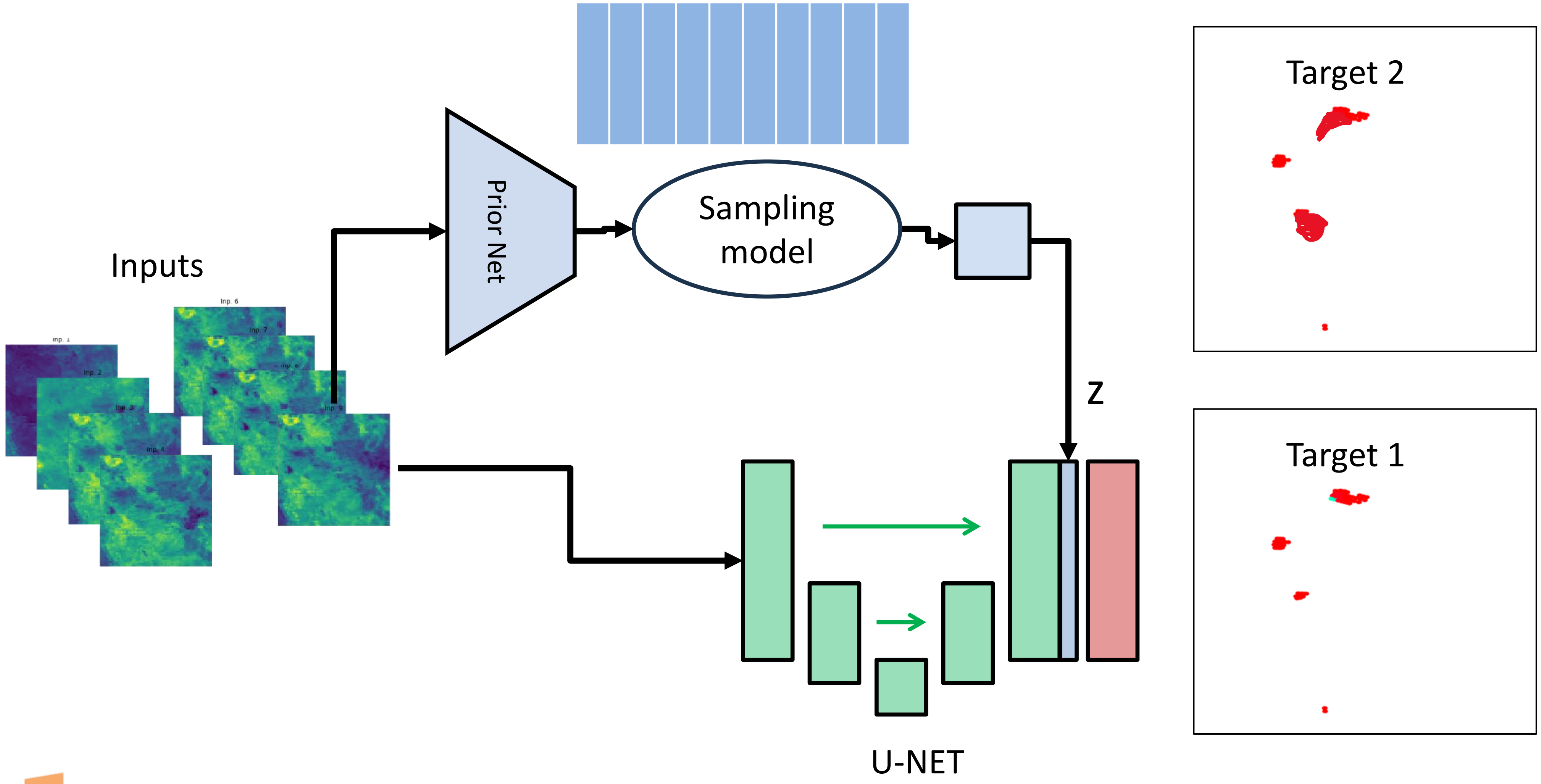
Figure 1: Left: A figure describing the VQ-VAE. Right: Visualisation of the embedding space. The output of the encoder $z(x)$ is mapped to the nearest point e_2. The gradient $\nabla_z L$ (in red) will push the encoder to change its output, which could alter the configuration in the next forward pass.

Van Den Oord, A., & Vinyals, O. (2017). Neural discrete representation learning. Advances in neural information processing systems, 30.

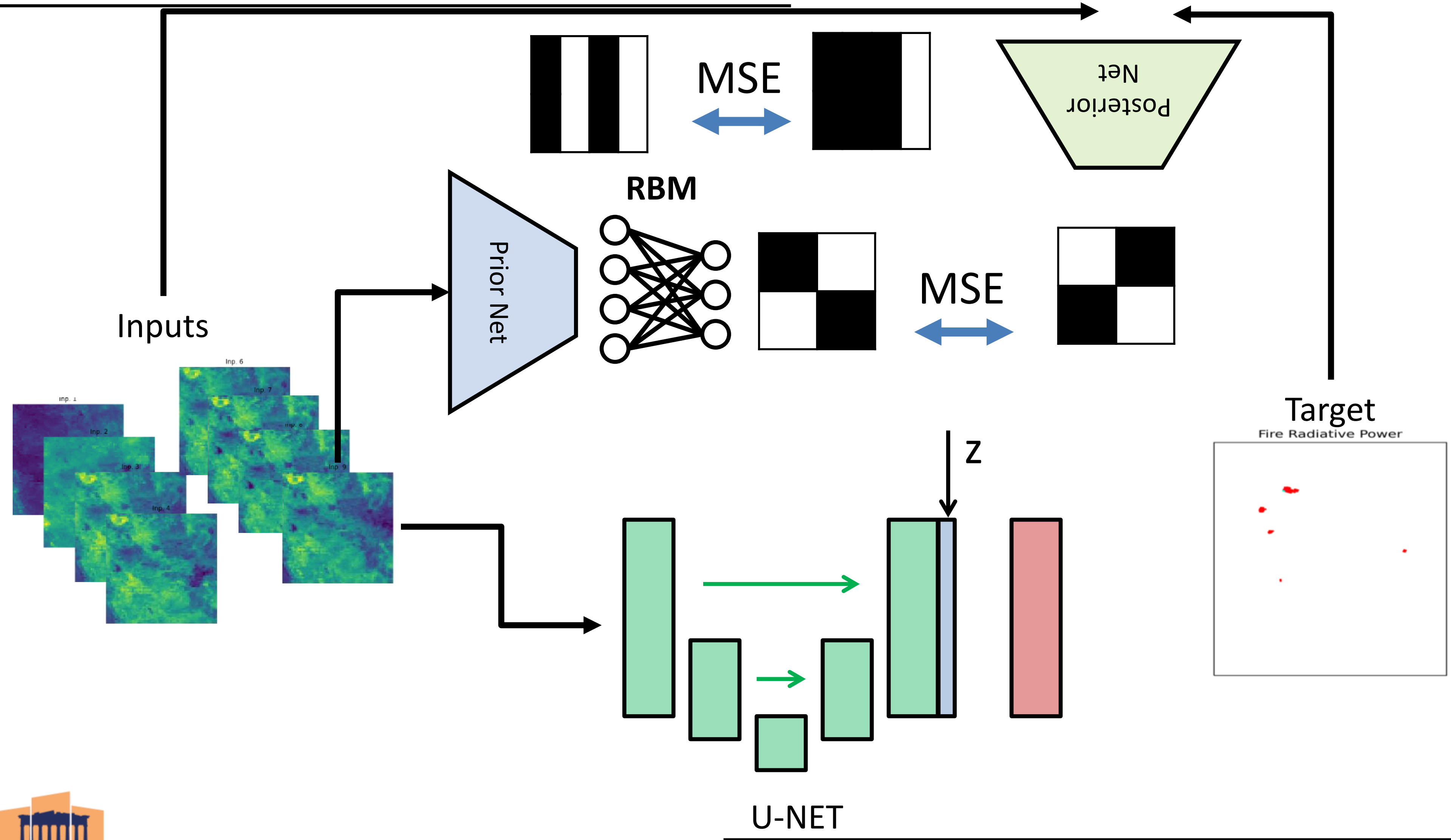
Vector Quantized U-NET – Training Mode



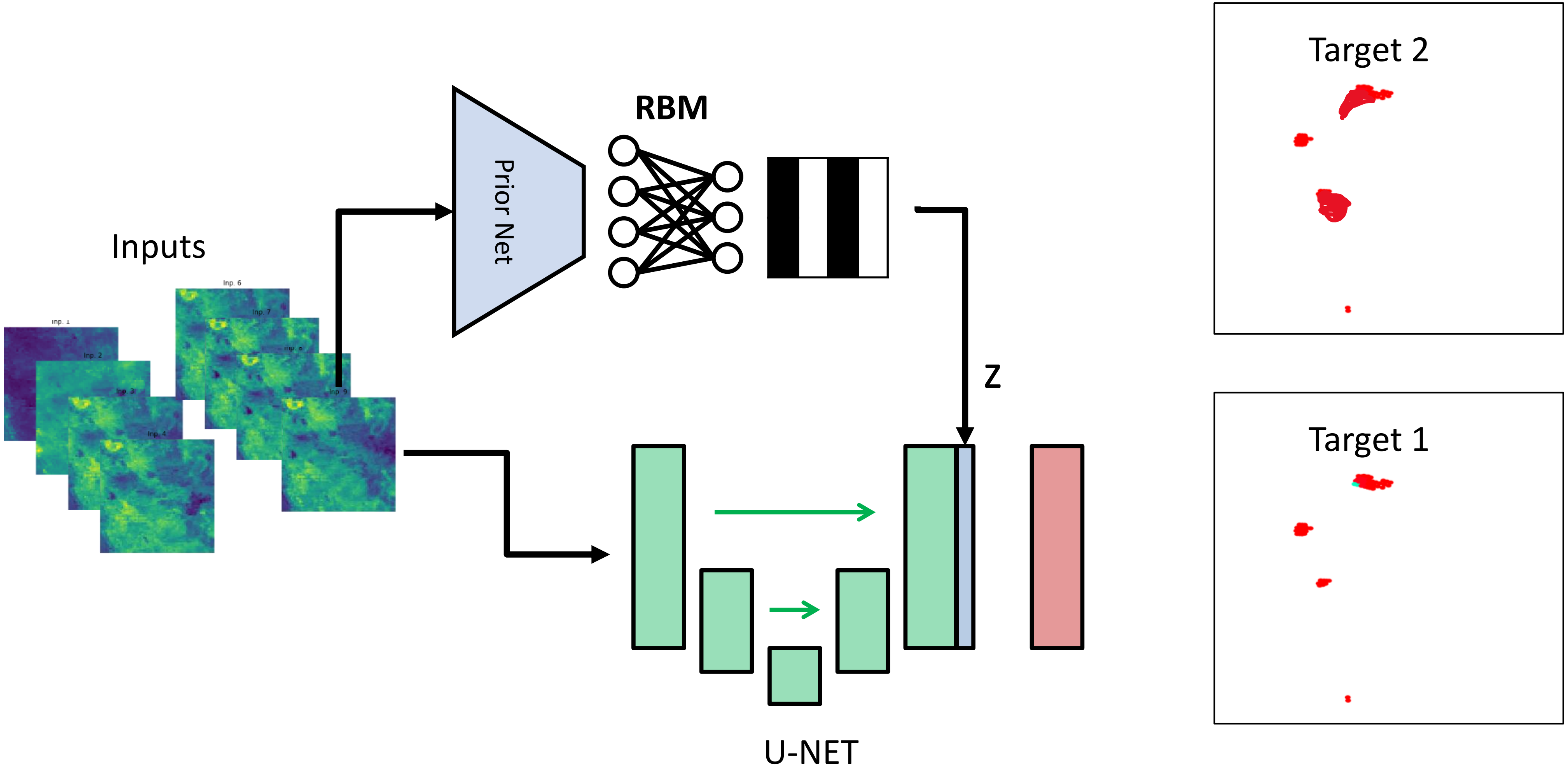
Vector Quantized U-NET (VQ-U-NET) – Inference Mode



Combining RBM with Vector Quantized U-NET – Training mode

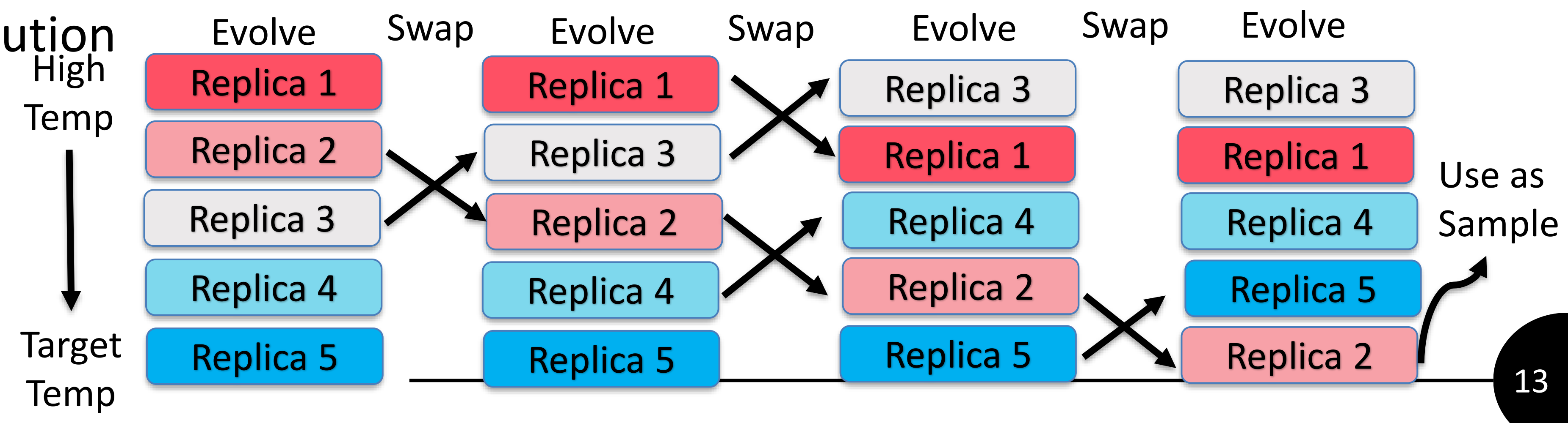


Combining RBM with Vector Quantized U-NET – Inference Mode



Parallel Tempering Integration with Probabilistic U-NET

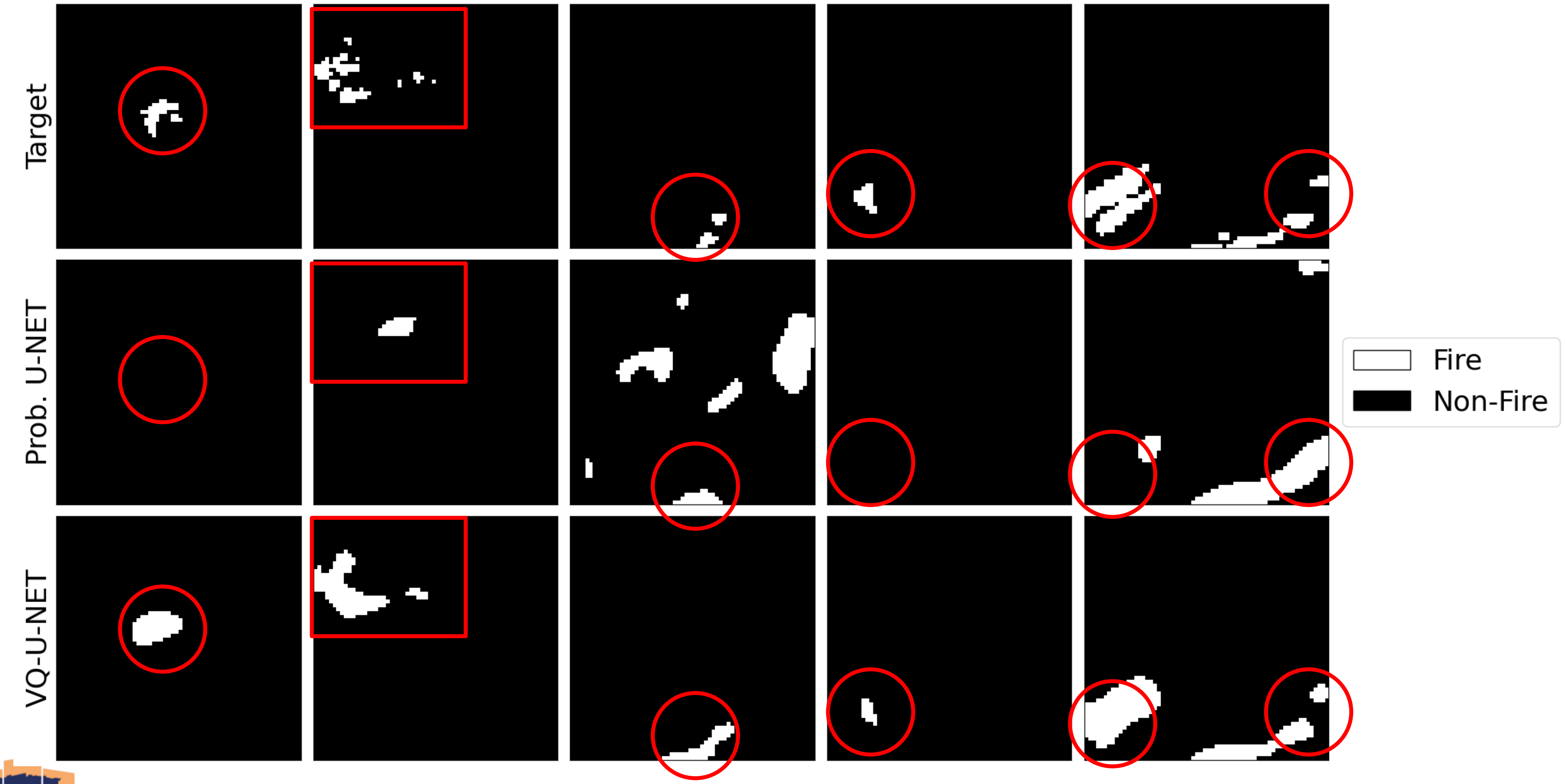
- Parallel Tempering is an importance sampling method and an alternative to Persistent Contrastive Divergence (PCD)
- This is a classical method used in Monte Carlo techniques and is implemented natively in PySA (https://github.com/nasa/PySA)
- It runs Markov chains of multiple replicas of the system at different temperatures, swapping states between temps
- This prevents the sampler from getting trapped in local minima and allows for better sampling of the distribution



Summary of Changes to VQ-VAE

- Re-organized VQ-VAE to become ***supervised***.
- Used a prior-posterior architecture to sync codebooks and encoders, further improving prior codebook and encoder performance.
- Added two more losses to the VQ-VAE triple losses to sync prior and posterior codebooks and encoder outputs.
- Binarized the encoder outputs and codewords.
- Added Restricted Boltzmann Machine (RBM) to prior encoder process.
- Switched from ancestral sampling to importance sampling via RBM.
- Trained RBM using Parallel Tempering.

Visual Comparison



Statistical Comparison

	Prob. U-NET	VQ-U-NET
Precision	51.36	59.24
Recall	57.64	69.2
F1-score	54.32	63.83

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1 score} = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

		Truth	
		Fire	No Fire
Prediction	Fire	TP	FP
	No Fire	FN	TN

Highlights

- Generative machine learning can improve our understanding of wildfire processes and offer a promising approach for wildfire detection.

- VQ-U-NET architecture provides an efficient approach to model wildfire with better segmentation representation.

- Physics-inspired approaches such as PySA can work effectively with discrete models such as VQ-VAE models even in a classical environment.

- Further efforts are required for evaluation of the introduced approach such as uncertainty analysis and model characteristics within continuous and discrete settings.

Acknowledgement & References

- This work is continuation of the NASA ESTO Advanced Information Systems Technology Program through grant AIST-QRS-21 and is supported by Quantum Intelligence Lab Group at NASA Ames.

- Van Den Oord, A., & Vinyals, O. (2017). Neural discrete representation learning. Advances in neural information processing systems, 30.
- Akbari Asanjan, A., Memarzadeh, M., Lott, P. A., Rieffel, E., & Grabbe, S. (2023). Probabilistic Wildfire Segmentation Using Supervised Deep Generative Model from Satellite Imagery. Remote Sensing, 15(11), 2718.
- Kohl, S., Romera-Paredes, B., Meyer, C., De Fauw, J., Ledsam, J. R., Maier-Hein, K., ... & Ronneberger, O. (2018). A probabilistic u-net for segmentation of ambiguous images. *Advances in neural information processing systems*, *31*.
- Khoshaman, A., Vinci, W., Denis, B., Andriyash, E., Sadeghi, H., & Amin, M. H. (2018). Quantum variational autoencoder. *Quantum Science and Technology*, *4*(1), 014001.

Thank you very much for your attention!

Questions?

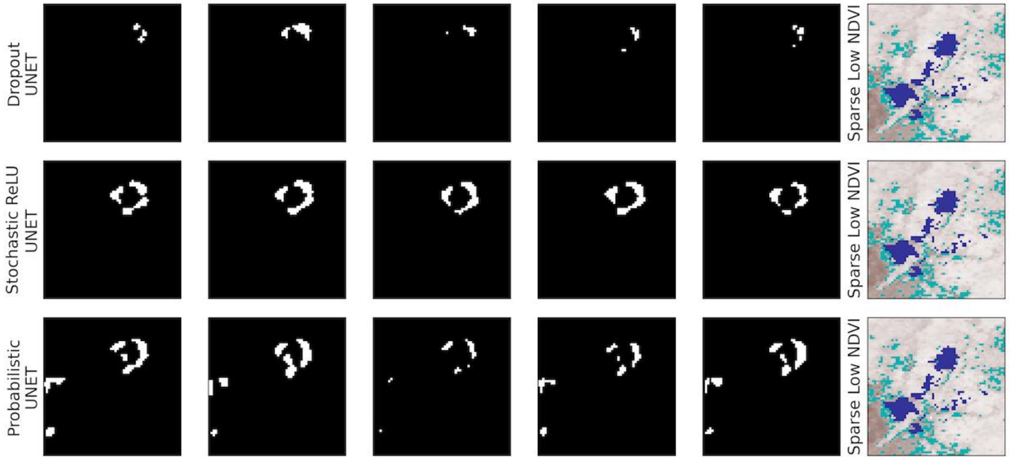
Ata Akbari Asanjan

ata.akbariasanjan@nasa.gov

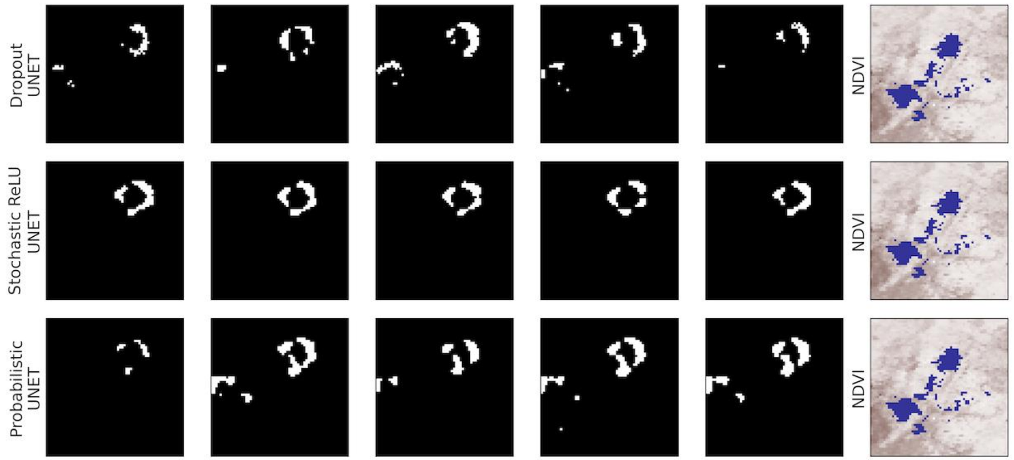
What-if Scenarios

Healthy Vegetation

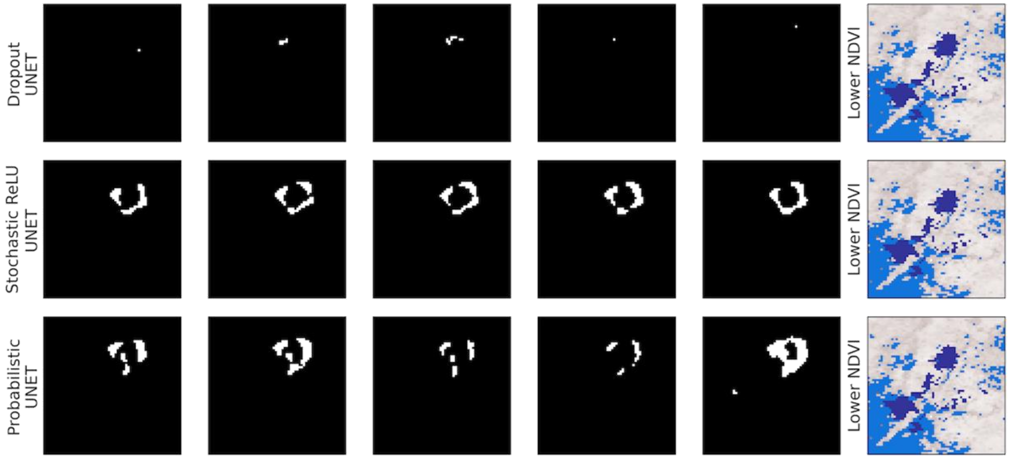
Sparse unhealthy Vegetation



Normal Vegetation



Very unhealthy/No Vegetation



Wildfires are stochastic in nature!

- Like many other natural processes, wildfires are stochastic.
- Wildfire simulations are classified in two categories:
  - **Deterministic**: Assuming wildfire processes are fully resolved.
    - Provides the same outcome every time the model is run for a single wildfire event.
    - Does not account for variability in observations.
  - **Stochastic**: Incorporates the variability of observation.
    - Provides different scenarios every time the model is run for a single wildfire event.
    - Provides a comprehensive statistical understanding for the variability over N runs.
- Thus, deterministic approaches are not optimal for stochastic processes (e.g. wildfire).

Credit: Kevin Maddrey

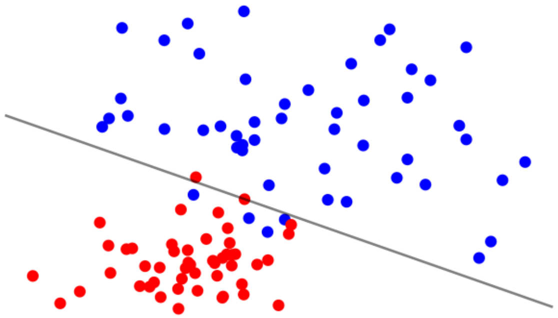
Uncertainty in Wildfire Observations

- Uncertainty analysis enables the assessment of reliability and confidence in research results.
- Uncertainty analysis aids in decision-making processes related to resource management, policy development, and risk assessment.
- It helps quantify and communicate the uncertainties associated with observations, measurements, and predictions in Earth science.

- However, uncertainty analysis is not cheap (requires extensive computational and design resources).
- Most uncertainty analysis methods are not designed to run “what-if” scenarios in a low-cost and comprehensive manner.

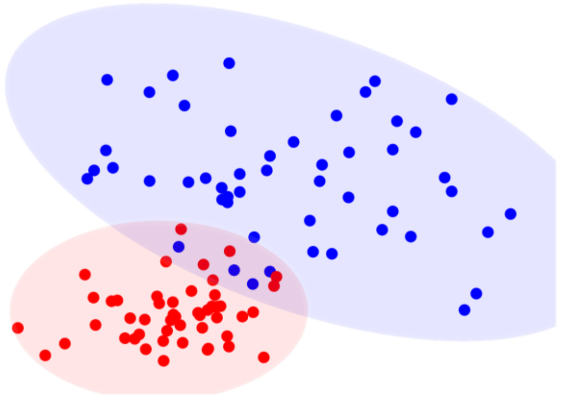
Discriminative vs. Generative

Discriminative modeling:



- In discriminative modeling, we aim to learn a model that discriminat (i.e. predicts) given the inputs. (In probability terms: $p(y \mid X)$)

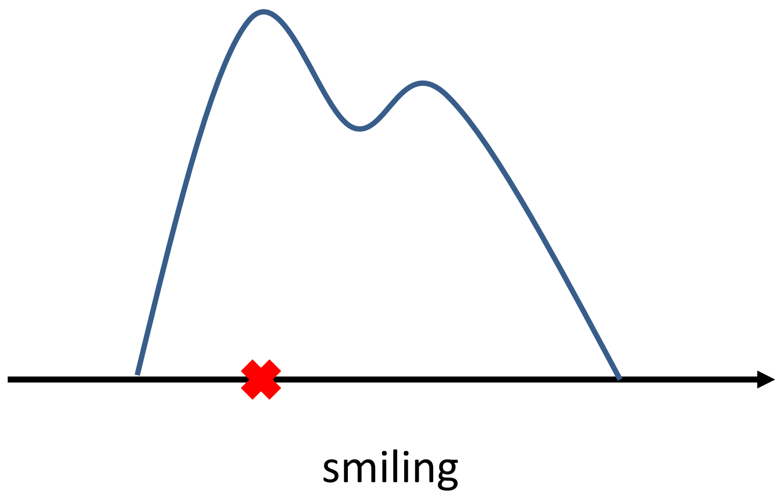
Generative modeling:

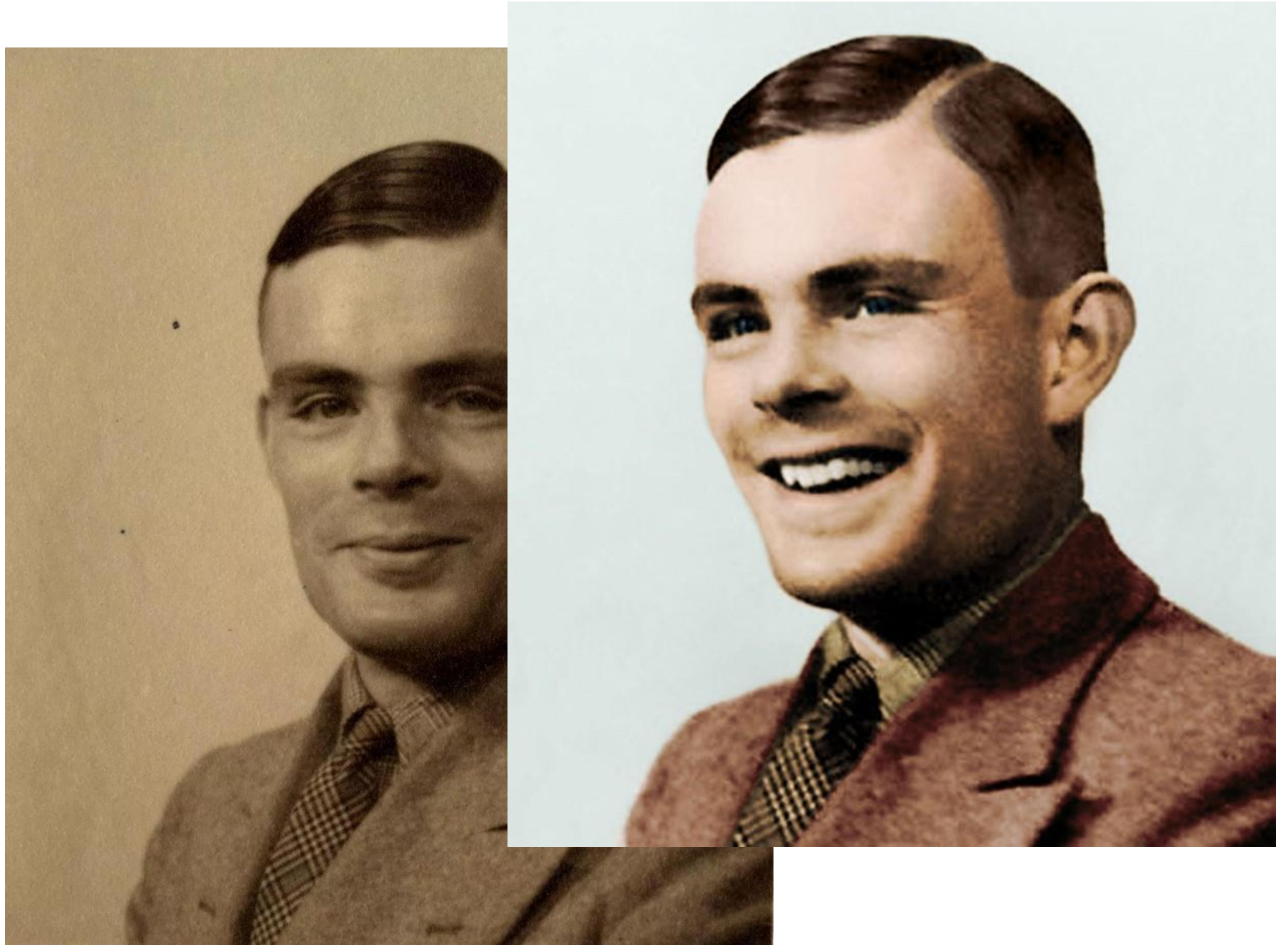


- Generative modeling aims to solve a more general problem. It aims to learn joint distribution over all variables.
(In probability terms: $p(y, X)$ or $p(y \mid X)\, p(X)$)
- A generative model simulates how the data is generated in the real world.

Generative Modeling based on Statistical Inference

Statistical Inference is a learning scheme in which we learn about an unobserved state based on our observations.





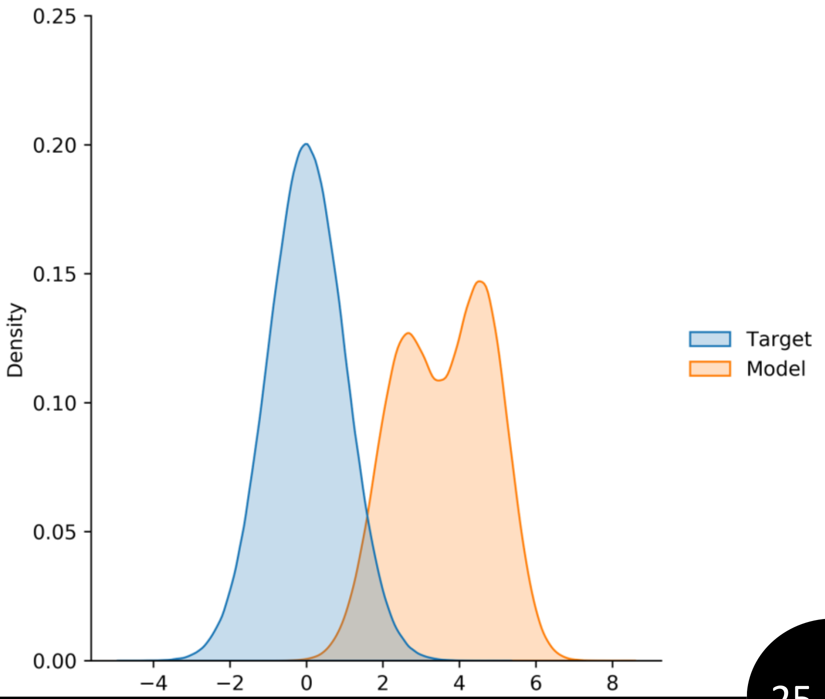
Variational Inference

Variational Inference suggests that instead of going through all the samples, we assume a distribution (e.g. Gaussian) from distribution family and instead of finding the entire distribution (hard), find the distribution parameters (easier).

$$p(x) = \int p(x \mid z)\, p(z)\, dz$$

How to measure the closeness of distributions?

We use a metric called Kullback-Leibler Divergence.



Generative Modeling based on Probabilistic Inference

Bayes rule:

$$p(z \mid x) = \frac{p(x \mid z)\, p(z)}{p(x)} = \frac{p(x, z)}{p(x)}$$

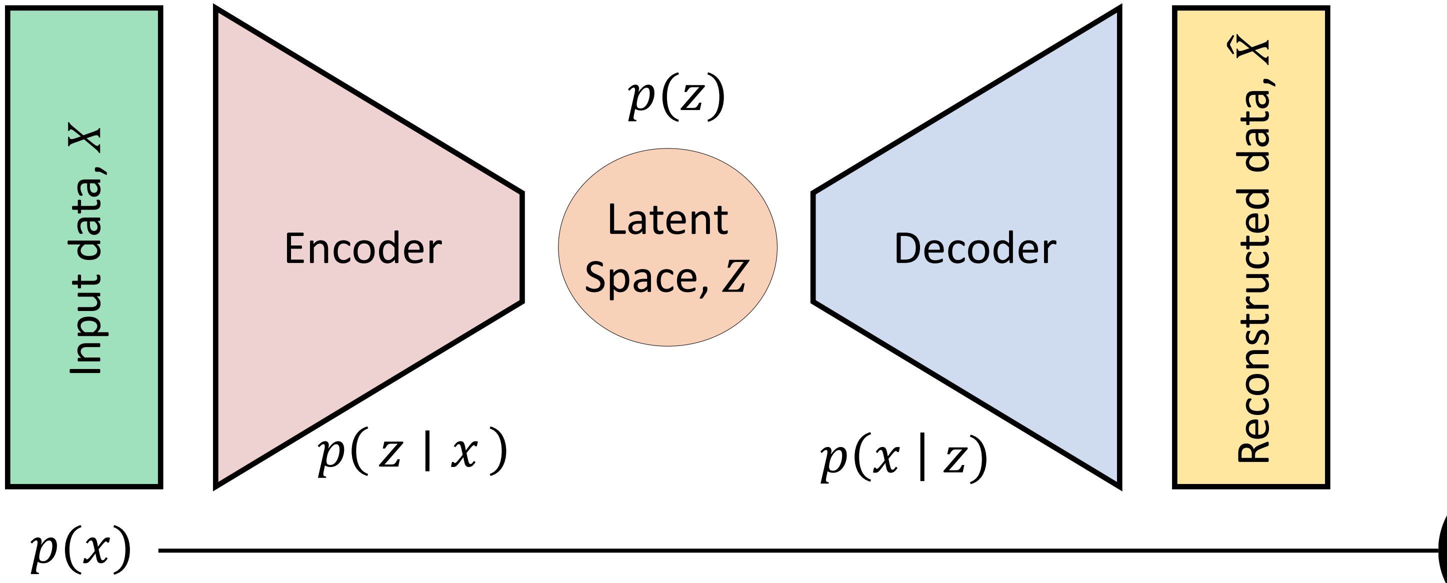
- $p(x)$ is data distribution or Evidence.
  - (In discriminative models, we rather focus on conditional probability $p(y|x)$ and neglect the unconditional probability $p(x)$.
- $p(z)$ is the prior distribution.
- $p(x \mid z)$ is the likelihood.
- $p(z \mid x)$ is posterior distribution.

Probabilistic Inference – Unsupervised Form

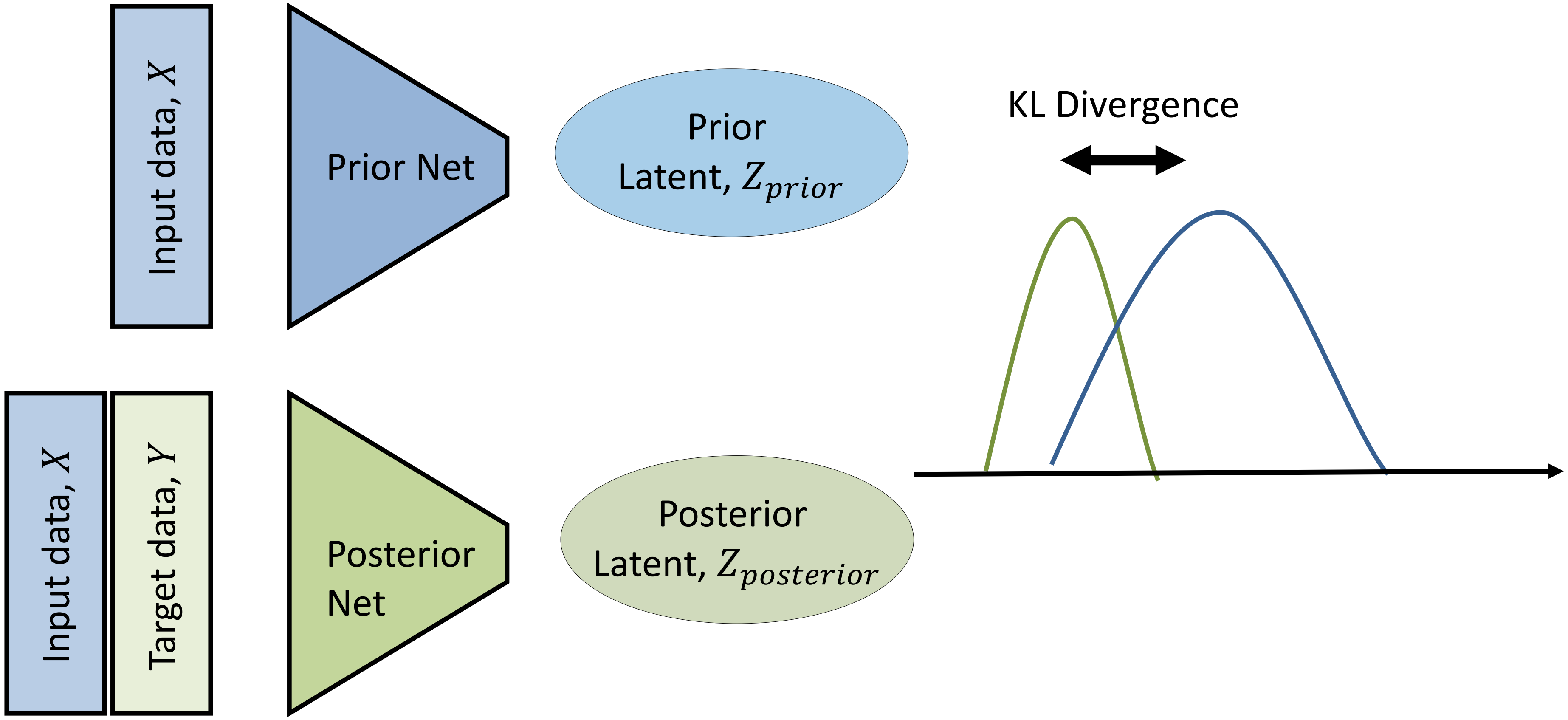
Bayes rule:

$$p(z \mid x) = \frac{p(x \mid z)\, p(z)}{p(x)} = \frac{p(x, z)}{p(x)}$$

In unsupervised variational inference we assume a family of distributions for the prior and force the model to learn the best distribution parameters that match the data.



Probabilistic Inference – Supervised Form



Probabilistic Inference – Supervised Form

- Probabilistic U-Net is a great approach for capturing variations in a supervised fashion.
- However, it can be further improved by relaxing the variation inference assumption (i.e. latent space is a Multivariate Gaussian distribution).
- In order to relax the prior assumption, we can replace the prior latent space with an iterative process such as Restricted Boltzmann Machine (RBM).
- The RBM allows parallel Gibbs sampling which results in more accurate prior characterization.
- This way we are joining the best of both worlds (Variational Inference & MCMC) to generate more accurate latent samples and thus, more realistic scenarios for wildfire detection.

Statistical Inference

Bayes rule:

$$p(z \mid x) = \frac{p(x \mid z)\, p(z)}{p(x)}$$

- Solving the Bayesian inference in the previous slide is often hard close to not possible.
- This becomes worst with larger dimensionality in data (e.g. Image, time series).

$$p(x) = \int p(x \mid z)\, p(z)\, dz$$

Solutions:

1. Variational Inference: Moderate accuracy, Fast
2. Markov Chain Monte Carlo: Good accuracy, Very slow

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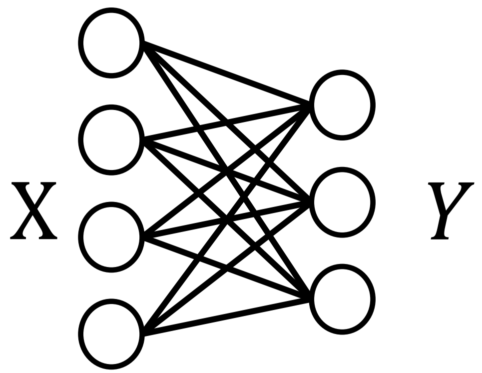
Gibbs Sampling in the form of ML

- Gibbs sampling can be implemented as a machine learning model.
- Imagine we have two variables X and Y.
- In order to sample from the joint $\mathrm{P}(X, Y)$ distribution, all we need is to have $\mathrm{P}(X \mid Y)$ and $\mathrm{P}(\mathrm{Y} \mid X)$.
- We can define a model that gives the conditional distributions: **Restricted Boltzmann Machine (RBM)**!
- RBM learns conditional distributions via negative log-likelihood.
- Gibbs sampler uses conditional distributions to refine samples.
- This mechanism learns a Boltzmann distribution of X and Y.

$$P(X, Y) = \frac{e^{-E(x)}}{\sum_{X,Y} e^{-E(x,y)}}$$



Monte Carlo Markov Chain

- MCMC is a generic method of sampling from a high-dimensional probability distribution.
- By sampling, we gain better knowledge of the entire probability distribution landscape.
- *As we sample more from a distribution,*

we learn more about the distribution!

- MCMC includes many variations
  - **Metropolis-Hasting**: Uses proposal density

  & acceptance/rejection method for new samples.
  - **Gibbs**: Uses conditional distributions for new samples. (Good for complex high-dimensional target distributions)

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Gibbs Sampling

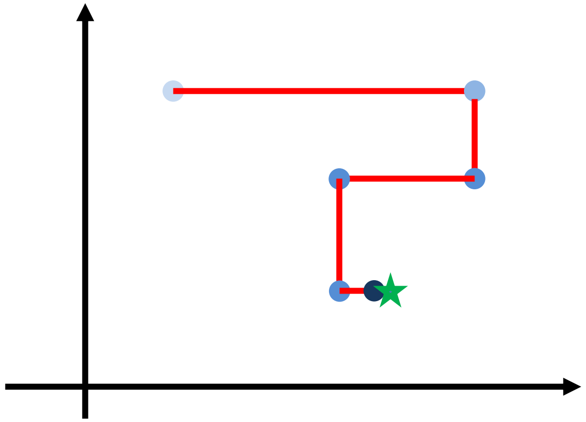
- Gibbs sampling breaks down the sampling process of a complex high-dimensional target distribution, into simpler, easy-to-sample conditional distributions.
  - Example: Imagine we have a N-d target distribution

$$P(x_1, x_2, x_3, \dots, x_N)$$

  - Drawing samples from this distribution is hard if we don't have the joint probability function.
  - Instead, we freeze all but one dimension and calculate a conditional probability. e.g.;

$$P(x_1 \mid x_2, x_3, \dots, x_N)$$

  - Then we start from a random location, update each dimension based on other given dimensions and conditional probability



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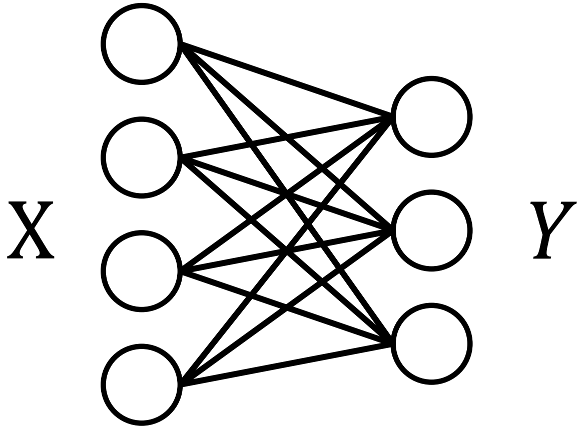
$$P(X, Y) = \frac{e^{-E(x)}}{\sum_{X,Y} e^{-E(x,y)}}$$



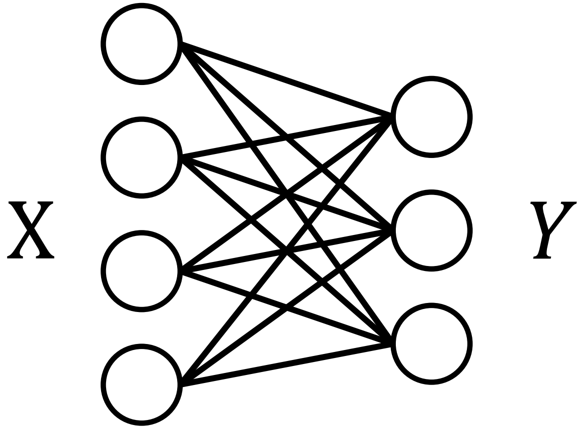
RBM: An energy-based model

- This mechanism learns a Boltzmann distribution of X.

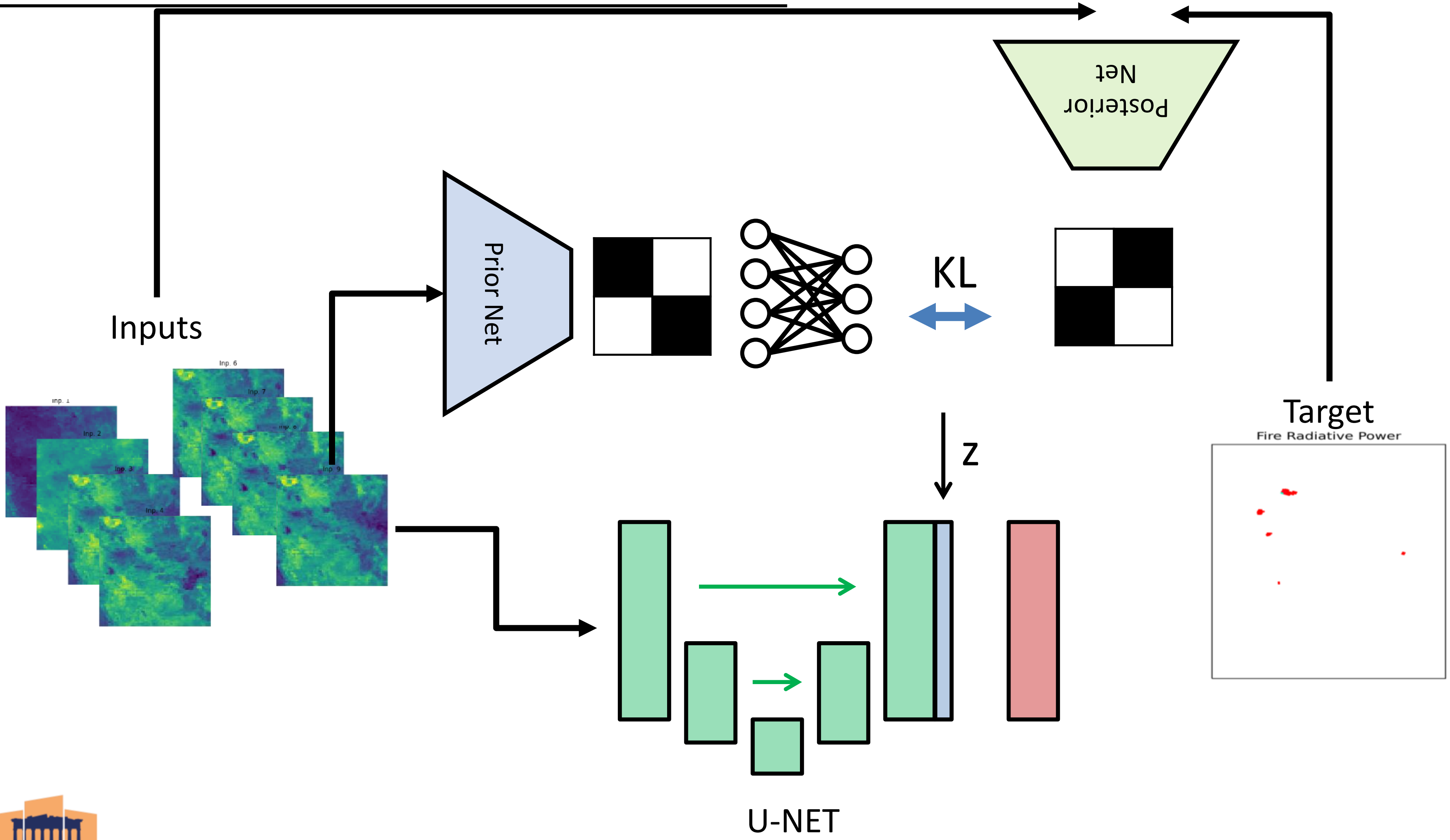
$$P(X) = \sum_{Y} \frac{e^{-E(x,y)}}{\sum_{X,Y} e^{-E(x,y)}}$$

- Energy term $E(x, y)$ can be represented by

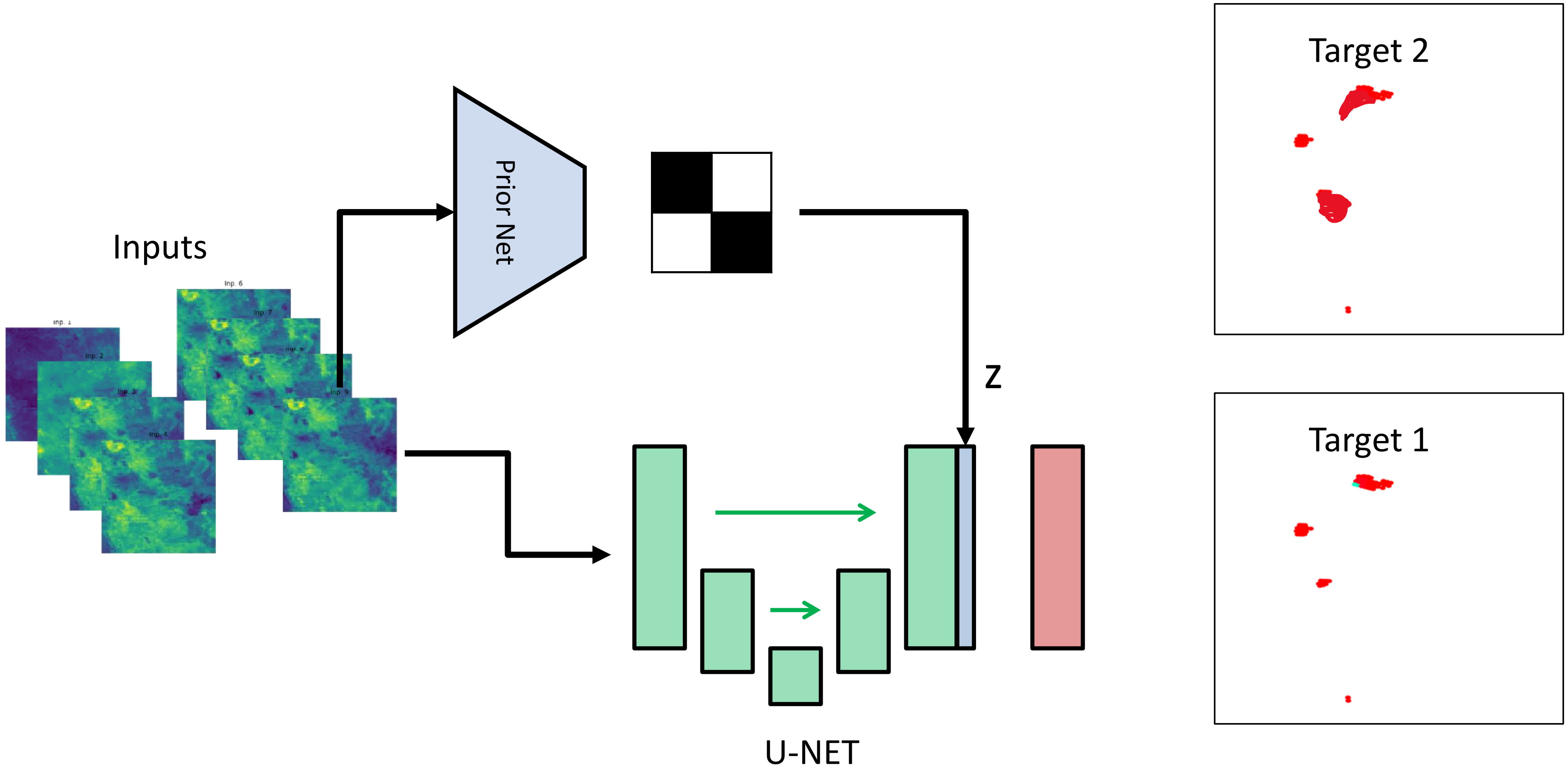
$$E(x,y) = -\sum_{i \in X} x_i\, b_i^X - \sum_{j \in Y} y_j b_j^Y - \sum_{i \in X} \sum_{j \in Y} x_i y_j w_{ij}$$



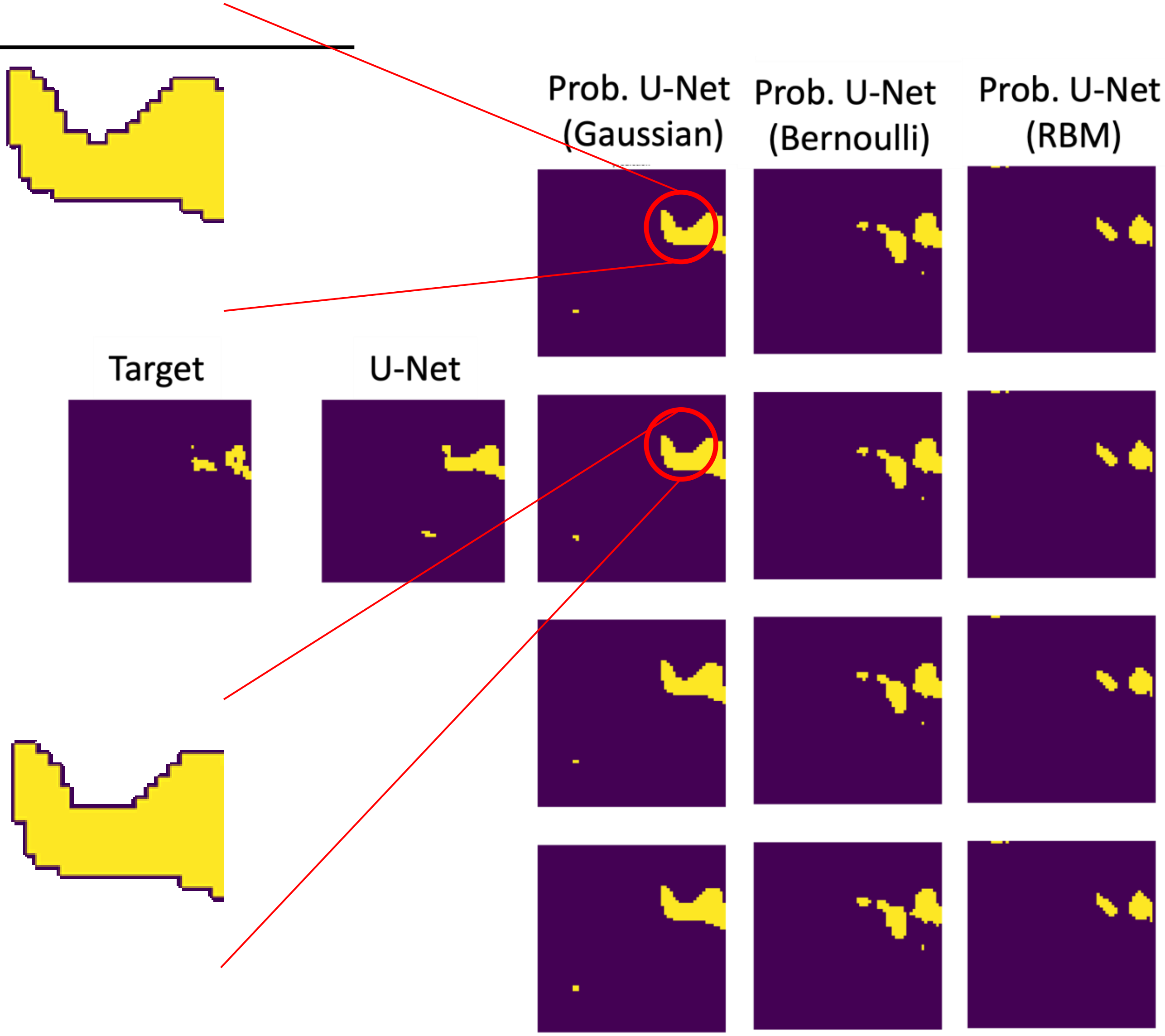
Combining RBM with Probabilistic U-Net – Training mode



Combining RBM with Probabilistic U-Net – Inference Mode



Visual Results



Performance Metrics

	U-Net	Prob. U-Net (Gaussian)	Prob. U-Net (Bernoulli)	Prob. U-Net (RBM)
Precision	0.536	0.431	0.235	**0.654**
Recall	**0.987**	0.955	0.752	0.473
F1 score	**0.695**	0.594	0.358	0.549
Jaccard score	**0.532**	0.422	0.318	0.378

Precision = $\frac{TP}{TP + FP}$

Recall = $\frac{TP}{TP + FN}$

F1 score = $\frac{2 \times Precision \times Recall}{Precision \times Recall}$

Jaccard score = $\frac{A \cap B}{A \cup B}$

		Truth	
		Fire	No Fire
Prediction	Fire	TP	FP
	No Fire	FN	TN

Advantages of the proposed approach

- Probabilistic U-Net with Boltzmann latent space is more generalized than its alike with Gaussian latent.
- Discrete latent space will help the model in efficient learning of latent configurations.
- RBM acts as a connection door between the classical and quantum computation realms.

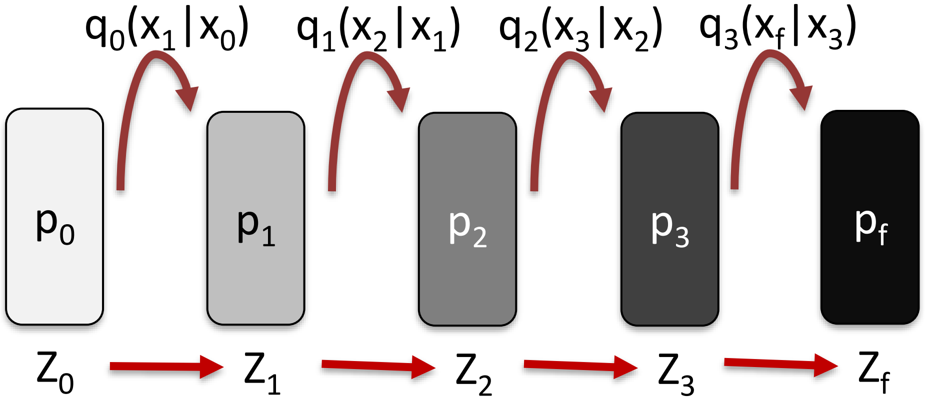
- ***Question**: How RBM connects classical and quantum computations?*
  - RBM uses $e^{-E(x)}$ to define probability, thus;

$$E(x) \propto \frac{1}{p}$$

  - Because of this property, we can look for lower energy to find higher probability samples.

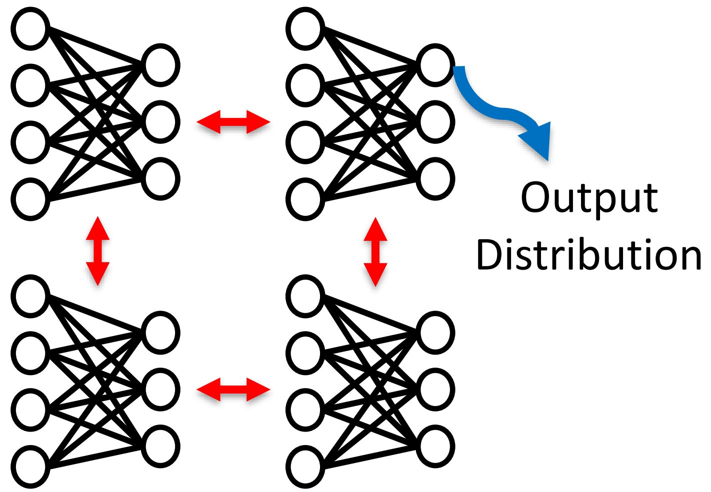
Annealed Importance Sampling

- Annealed Importance Sampling (AIS) is an alternative to Parallel Tempering or Persistent Contrastive Divergence
- It changes the distribution slowly from a reference distribution to a target distribution in an even way such that importance weights can be calculated
- This method allows you to estimate the partition function, giving a way of gauging the quality of your sampling
- We have implemented AIS in PySA and have ported over its partition function estimation to parallel tempering, allowing for similar calculations there



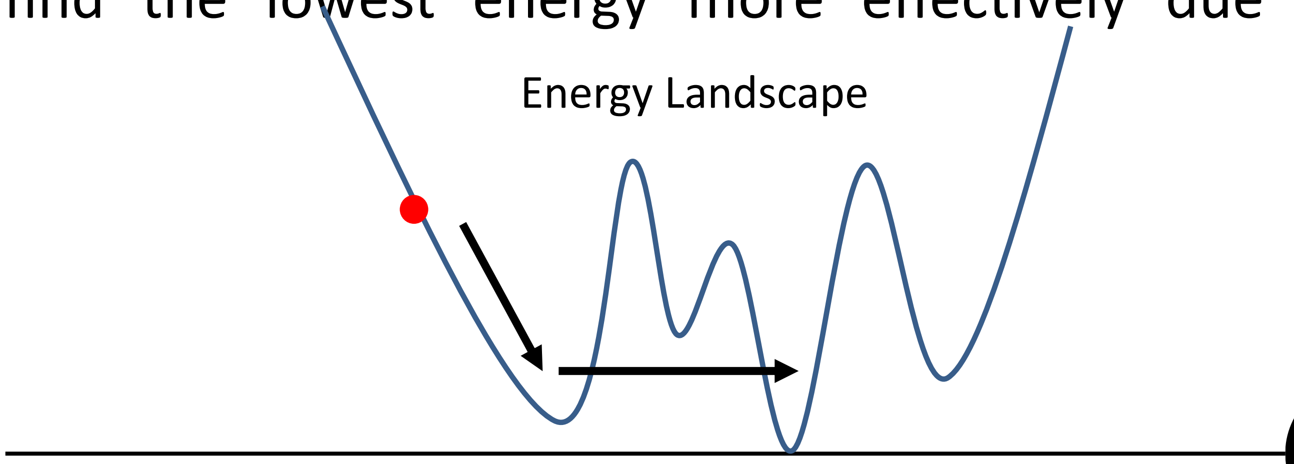
Path-Integral Quantum Monte Carlo Integration with Probabilistic U-Net

- Quantum Monte Carlo (QMC) is a classical technique of using Markov Chain Monte Carlo to sample from a quantum thermal distribution.
- This is equivalent to an RBM, just where the RBM can have both thermal and quantum effects.
- Classical simulation of Quantum RBMs via QMC is efficient but offers more power than exists in classical RBMs
- In practice this can be visualized as multiple RBMs working together to get results
- This has been implemented in PySA and can be integrated with the Prob. U-Net as a different sampler.



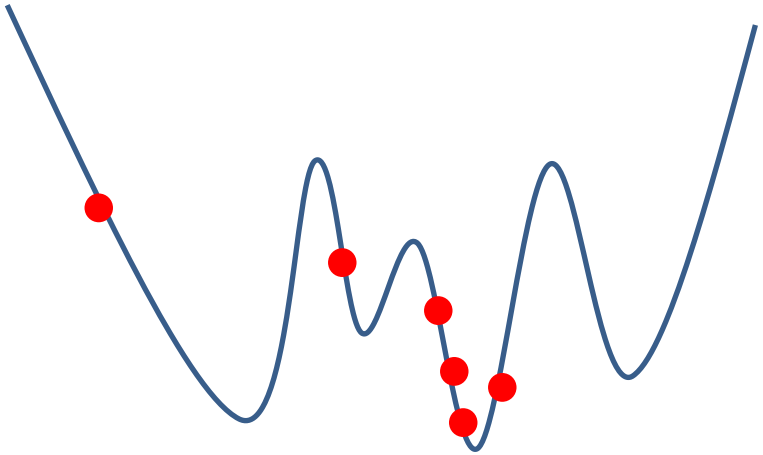
Quantum Computation

- Quantum computing is a rapidly emerging technology based on quantum mechanics.
- Multiple applications, such as optimization and sampling, have been introduced and are expected to surpass the classical computers' performances.
- Quantum annealing is a proposed optimization method for finding the lowest energy (best answer).
- We start from an initial Hamiltonian state and slowly move toward problem Hamiltonian (solution).
- Theoretically, quantum computer can find the lowest energy more effectively due to tunneling effect.

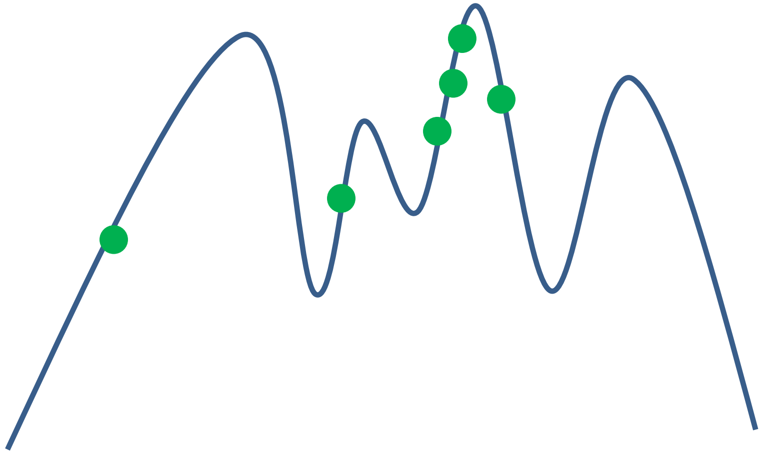


Bridge between Quantum and Classical Computation

- We can use this property in sampling to find the best Boltzmann distribution.
- We do MCMC in Energy landscape to find the lowest energy point. That is equivalent to doing MCMC on Boltzmann distribution.
- This approach is expected to perform better because of Quantum computer's effective and fast sampling.
- The results are expected to be more accurate and simultaneous.



Energy Landscape



Probability Distribution