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Session 6: Frontiers in Probabilistic Machine Learning

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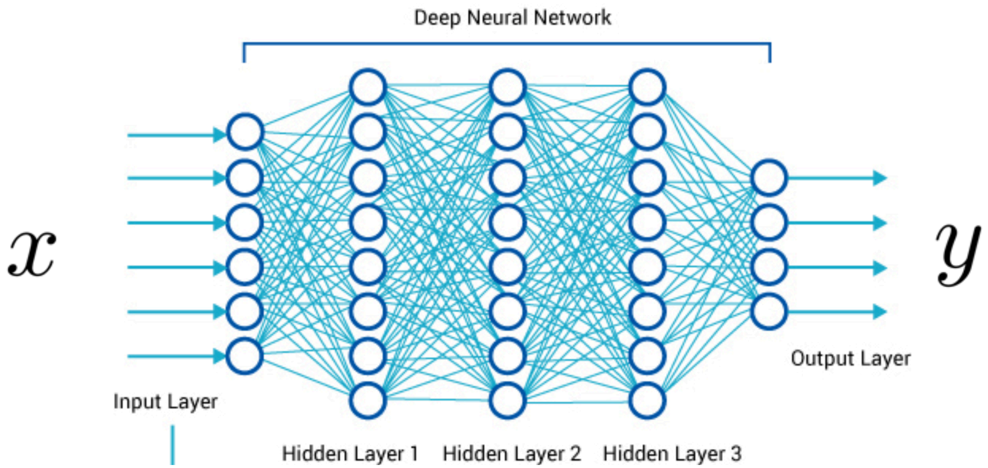
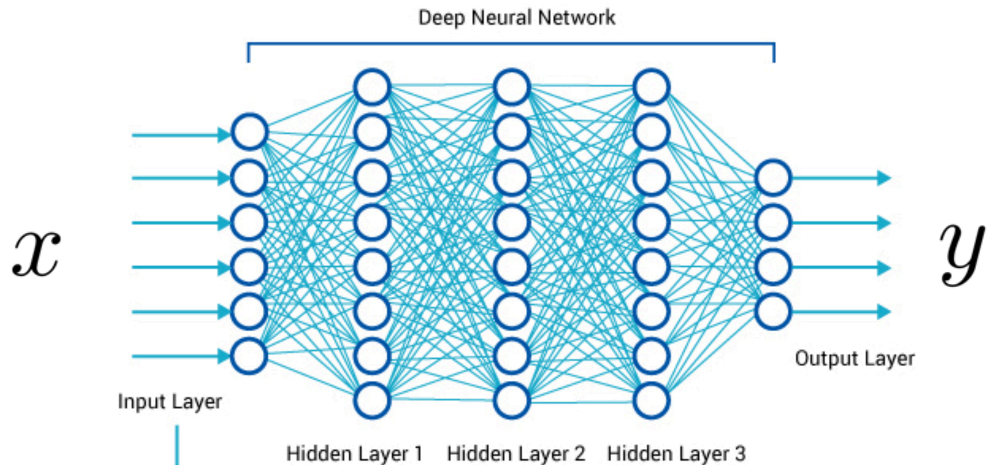
Bayesian Deep Learning


Deep Neural Network
x
y
Input Layer
Hidden Layer 1
Hidden Layer 2
Hidden Layer 3
Output Layer

$$p(y|x,\theta)$$



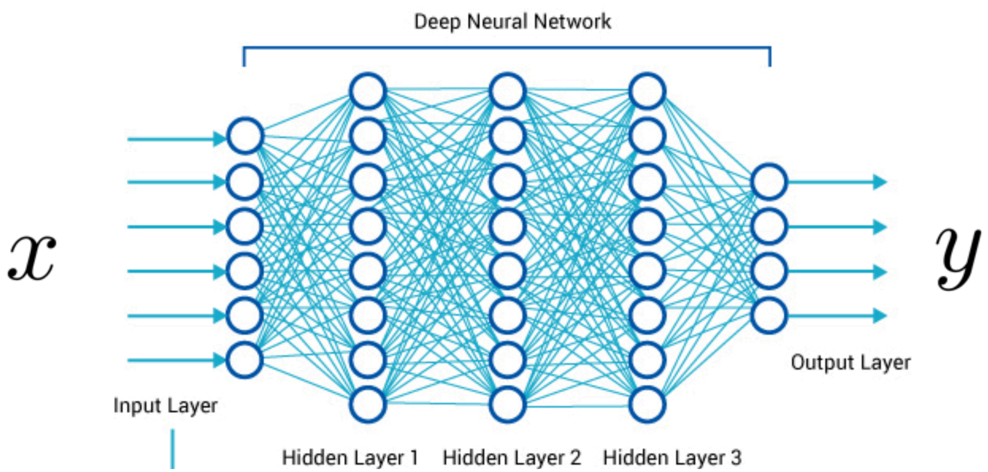
$$p(y|x,D) = \int p(y|x,\theta)p(\theta|D)d\theta$$

Deep Learning + Bayesian modeling

Powered by new advances in variational inference

(e.g. variational autoencoders, black-box variational inference, adversarial training,etc.).

Bayesian Deep Learning



$$p(y|x,D) = \int p(y|x,\theta)p(\theta|D)d\theta \approx \sum_i p(y|x,\theta_i)w_i$$

Deep Learning + Bayesian modeling

Powered by new advances in variational inference

(e.g. variational autoencoders, black-box variational inference, adversarial training,etc.).

Bayesian Deep Learning

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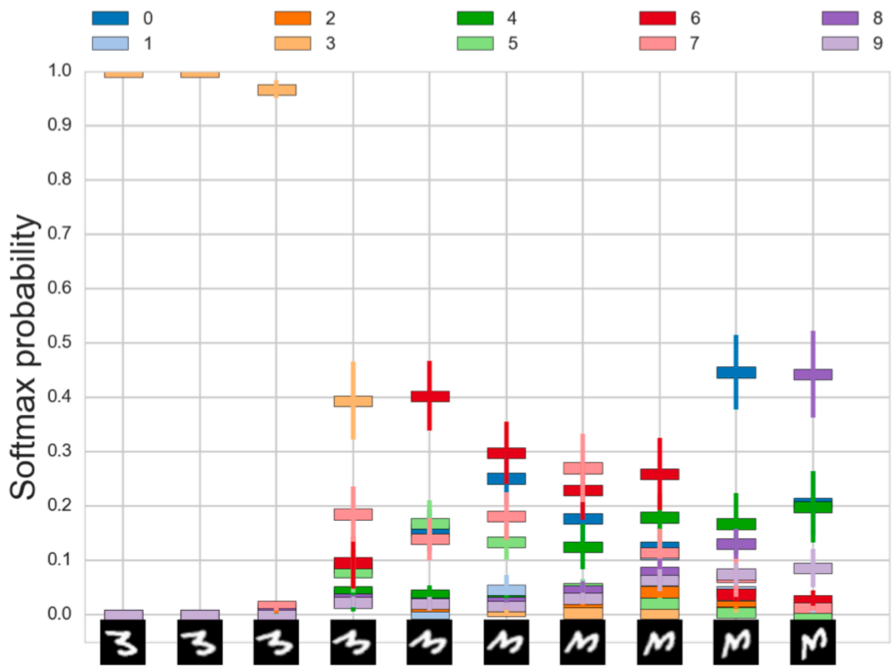
Louizos C. et al. ***Multiplicative Normalizing Flows for Variational Bayesian Neural Networks.*** *ICML 2017*

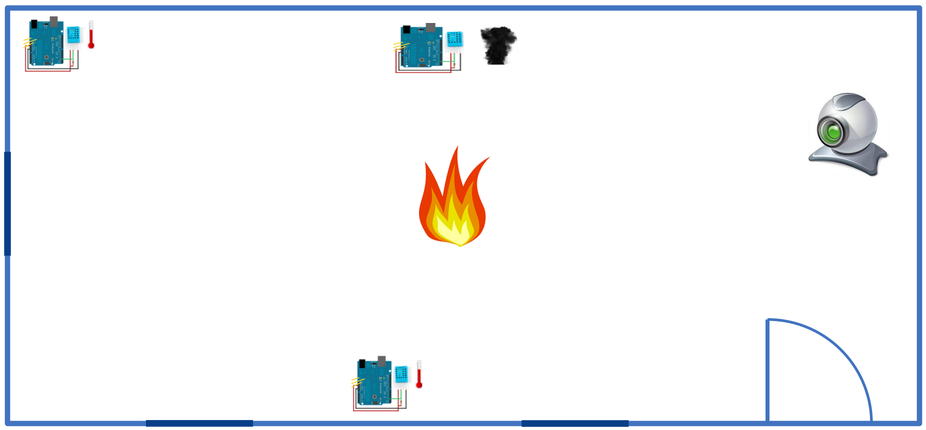
BAYESIAN DEEP LEARNING



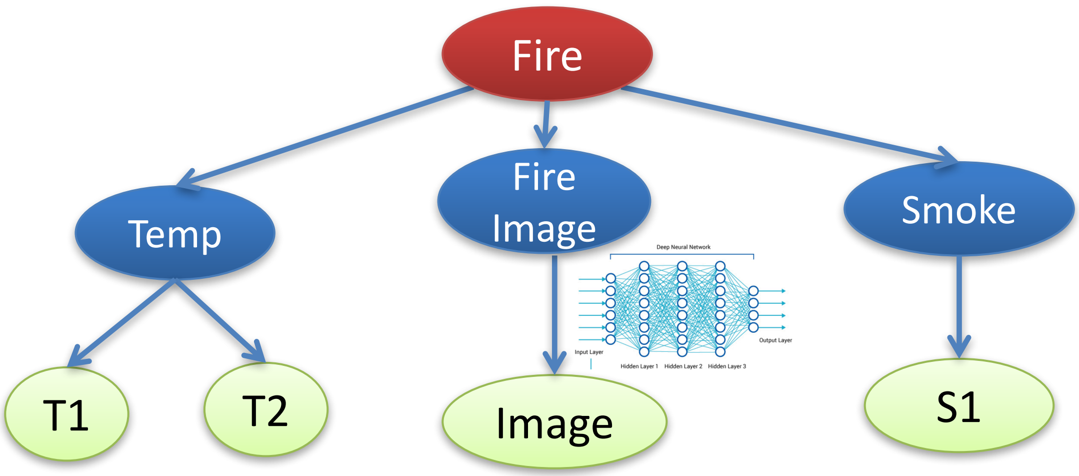
Louizos C. et al. ***Multiplicative Normalizing Flows for Variational Bayesian Neural Networks.*** *ICML 2017*

Probabilistic Modelling with Deep Neural Networks

Fire Detection from smoke, temperature and camera sensors



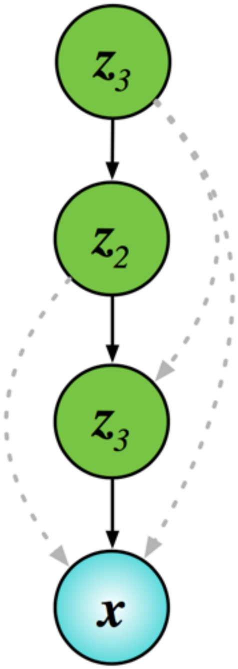
- Data Collected
  - Tons of observations in normal settings (no fire).
  - No observations in the presence of fire.



$$p(Fire = True | t_1, t_2, t_3, s_1, image)$$

Much more expressive and powerful models

- Beyond standard probability distribution assumptions.
- Modelling highly-non linear relationships.

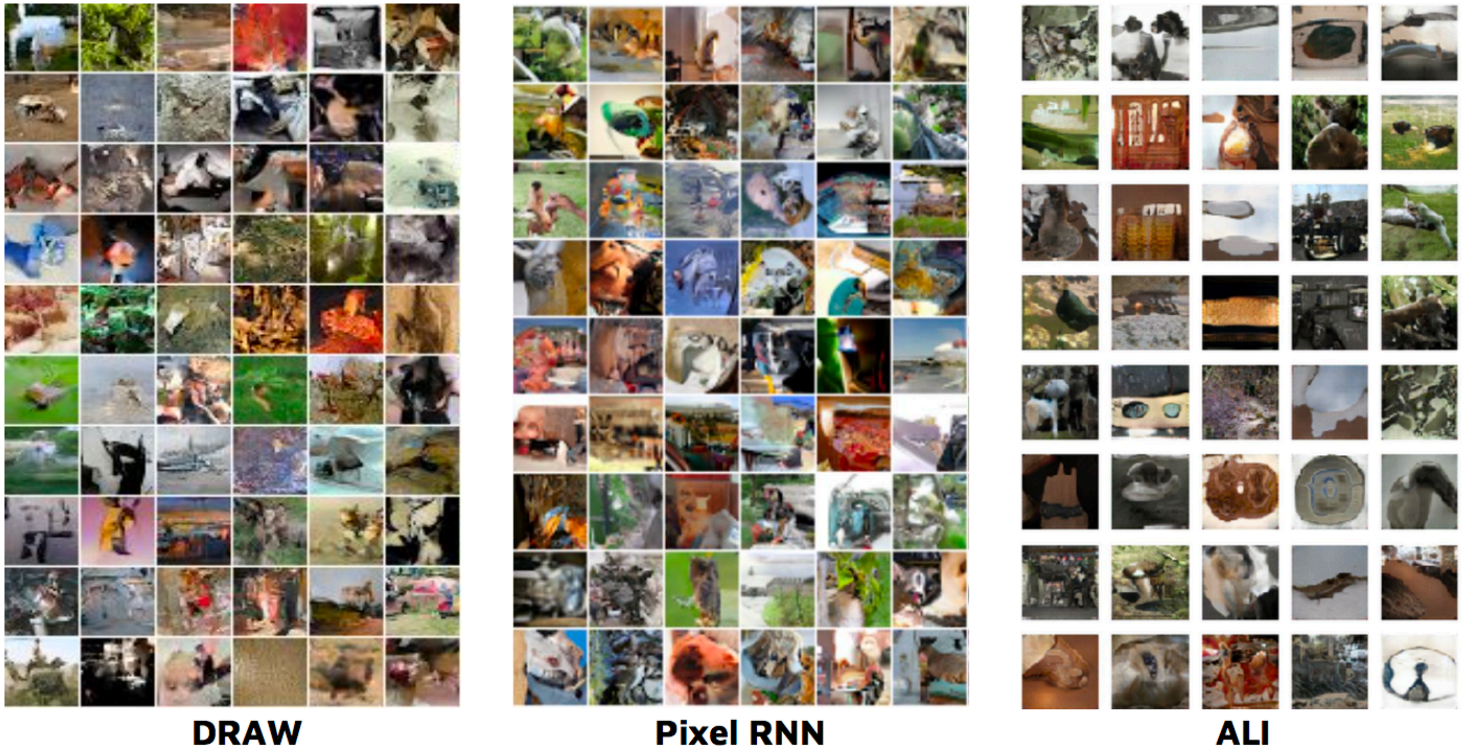


$$\mathbf{z}_3 \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$$
$$\mathbf{z}_2 | \mathbf{z}_3 \sim \mathcal{N}(\mu(\mathbf{z}_3), \Sigma(\mathbf{z}_3))$$
$$\mathbf{z}_1 | \mathbf{z}_2 \sim \mathcal{N}(\mu(\mathbf{z}_2), \Sigma(\mathbf{z}_2))$$
$$\mathbf{x} | \mathbf{z}_1 \sim \mathcal{N}(\mu(\mathbf{z}_1), \Sigma(\mathbf{z}_1))$$

Deep Generative Models

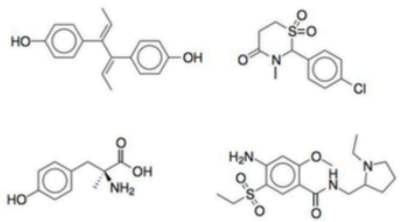
- Model Complex joint distributions over data.
- GANs can be interpreted as generative models.

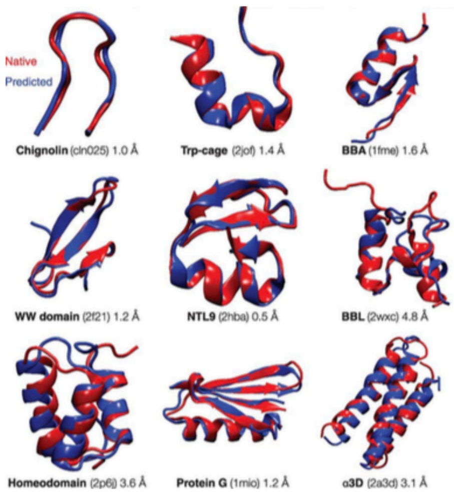
Generating images and video content.

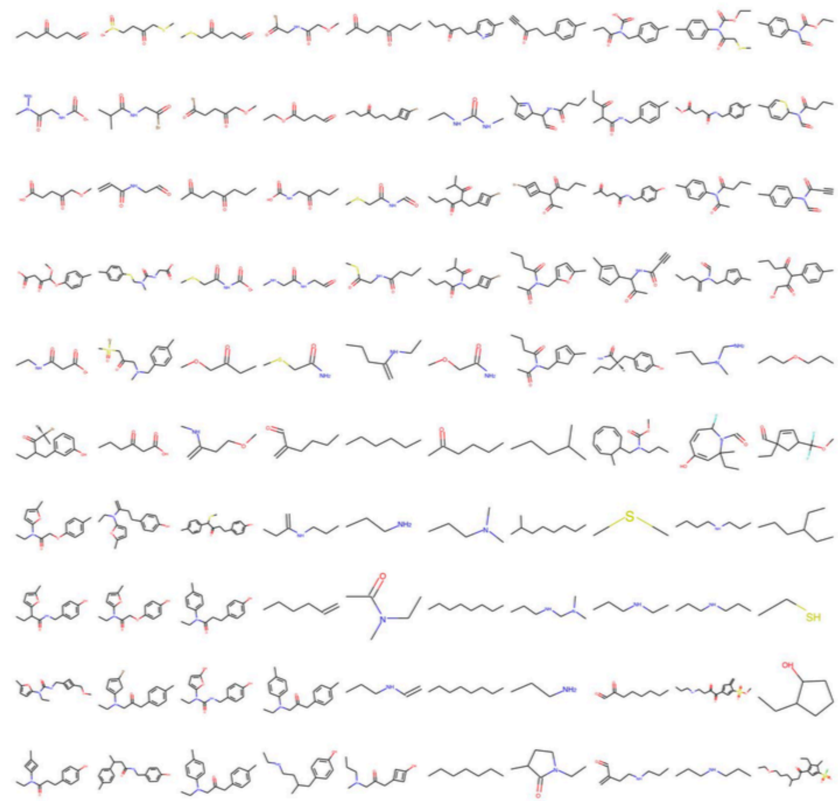


Gregor et al., 2015, Oord et al., 2016, Dumoulin et al., 2016

Drug Design

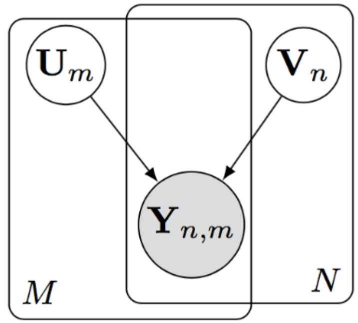






Gómez-Bombarelli, et al. 2016

Probabilistic Programming Languages




```
N = 10
M = 10
K = 5  # latent dimension

U = Normal(mu=tf.zeros([M, K]), sigma=tf.ones([M, K]))
V = Normal(mu=tf.zeros([N, K]), sigma=tf.ones([N, K]))
Y = Normal(mu=tf.matmul(U, V, transpose_b=True), sigma=tf.ones([N, M]))
```

Tran, Dustin, et al. "Edward: A library for probabilistic modeling, inference, and criticism." *arXiv preprint arXiv:1610.09787* (2016).

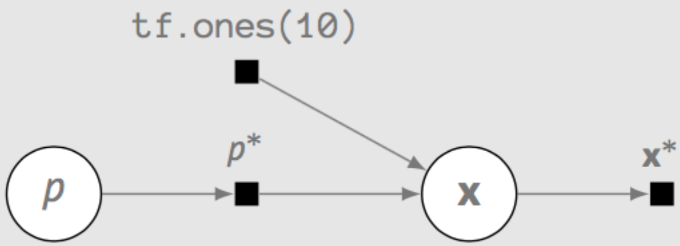
Probabilistic Programming Languages

- More powerful probabilistic modeling (e.g. Turing complete).
- Boost the productivity of data scientists.
- Expand the use of probabilistic modeling to non-experts.

Model code

```
p = Beta(a=1.0, b=1.0)
x = Bernoulli(p=tf.ones(10) * p)
```

Computational graph



Edward: Probabilistic Programming with TensorFlow

- Probabilistic Code compiled to (Stochastic) Computational Graph.
- Speed-up due to GPU computations.

Generative model

```
from edward.models import Bernoulli, Normal
from keras.layers import Dense

z = Normal(mu=tf.zeros([N, d]), sigma=tf.ones([N, d]))
h = Dense(256, activation='relu')(z.value())
x = Bernoulli(logits=Dense(28 * 28)(h))
```

Edward: Probabilistic Programming with TensorFlow

- Probabilistic Code compiled to (Stochastic) Computational Graph.
- Speed-up due to GPU computations.

Probabilistic Programming

Edward

TensorFlow

PyMC3

theano

InferPy

Edward

Keras

PYTORCH

Causal Learning

CAUSALITY

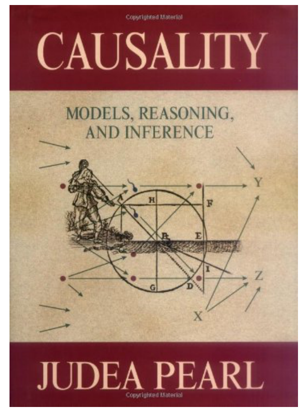
"I would rather discover one causal relation than be King of Persia"

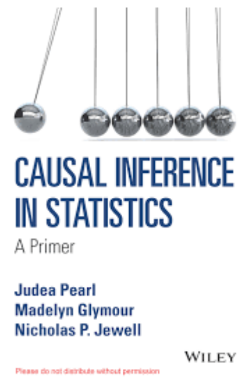
Democritus (430-380 BC)

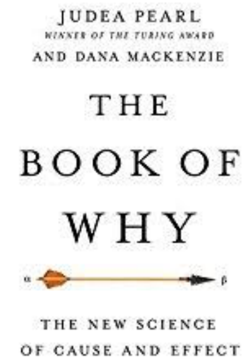
Development of Western science is based on two great achievements: the invention of the formal logical system (in Euclidean geometry) by the Greek philosophers, and the discovery of the possibility to find out causal relationships by systematic experiment (during the Renaissance).

A. Einstein, April 23, 1953

Causal Learning







Discover Causality relationships from observational data

Thanks for your attention

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