敏捷建模：算力-算法-灰度

关键词：Computing Force、混沌、信息流、SVI

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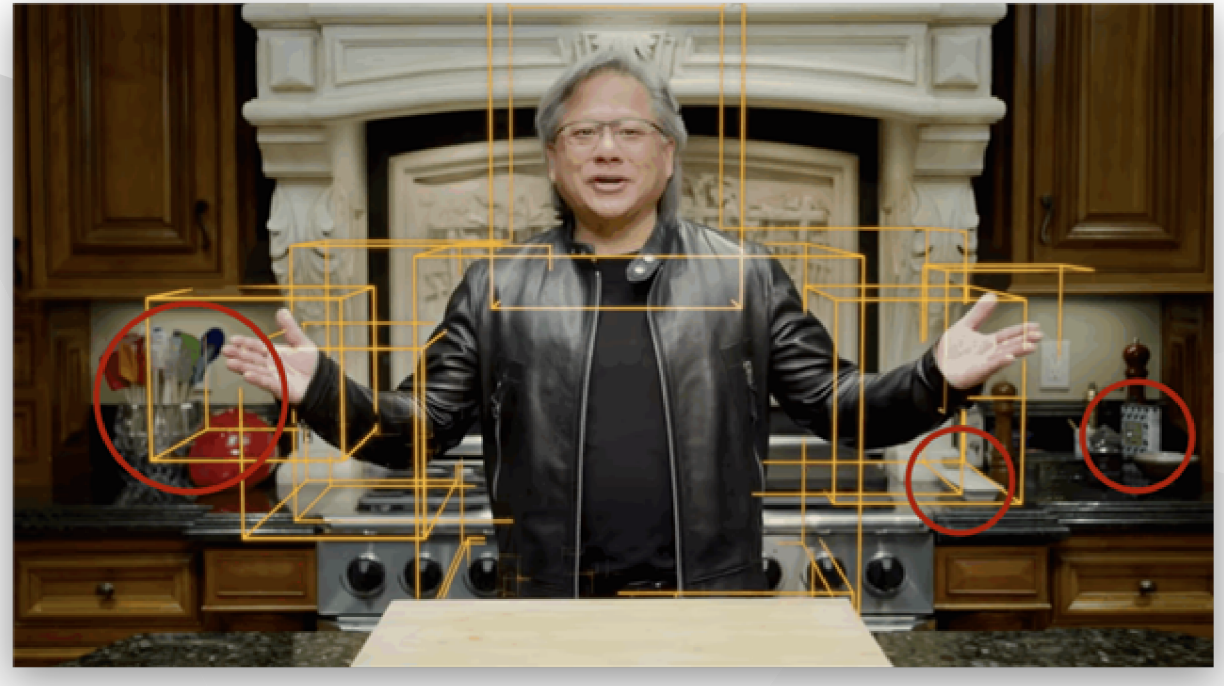
Available at https://github.com/SmartDataLab/CF-Share

Written by Marp and Mermaid in Markdown

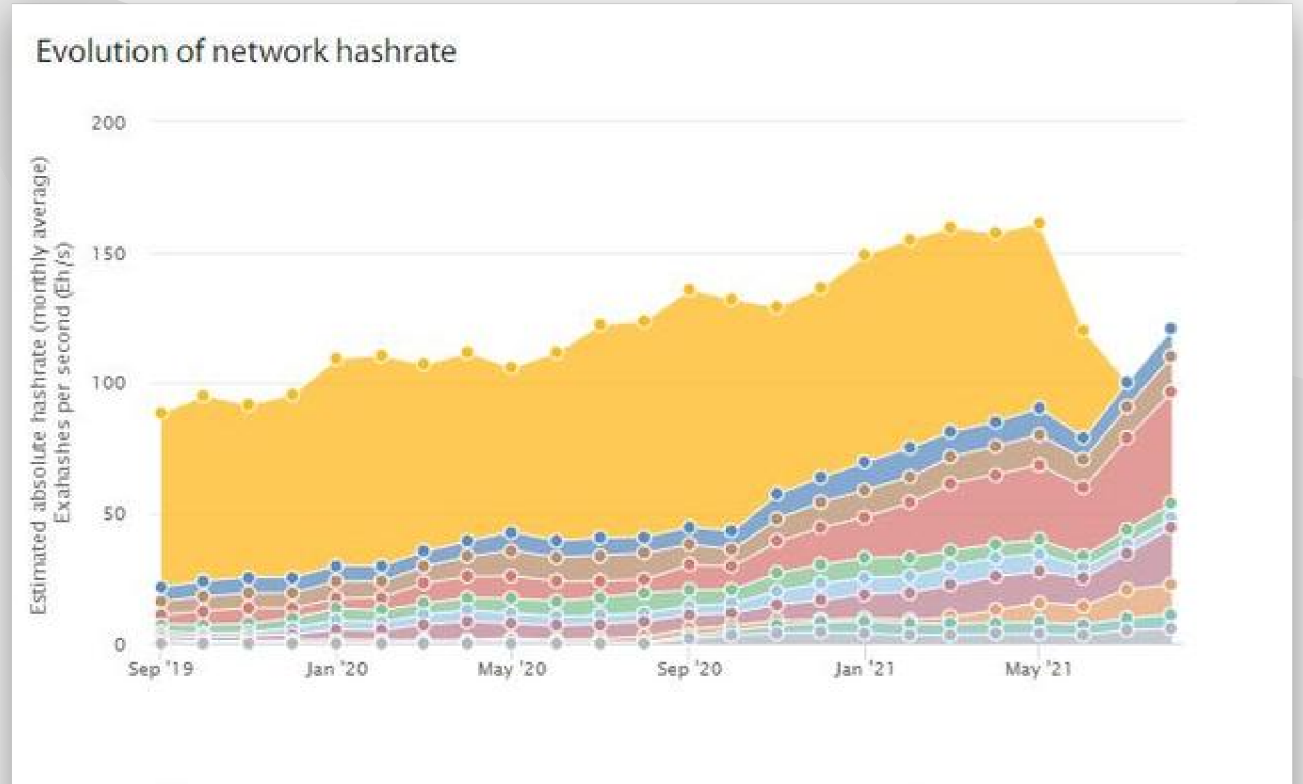
厨房、皮衣与矿池

- 游戏党与年度最佳投资



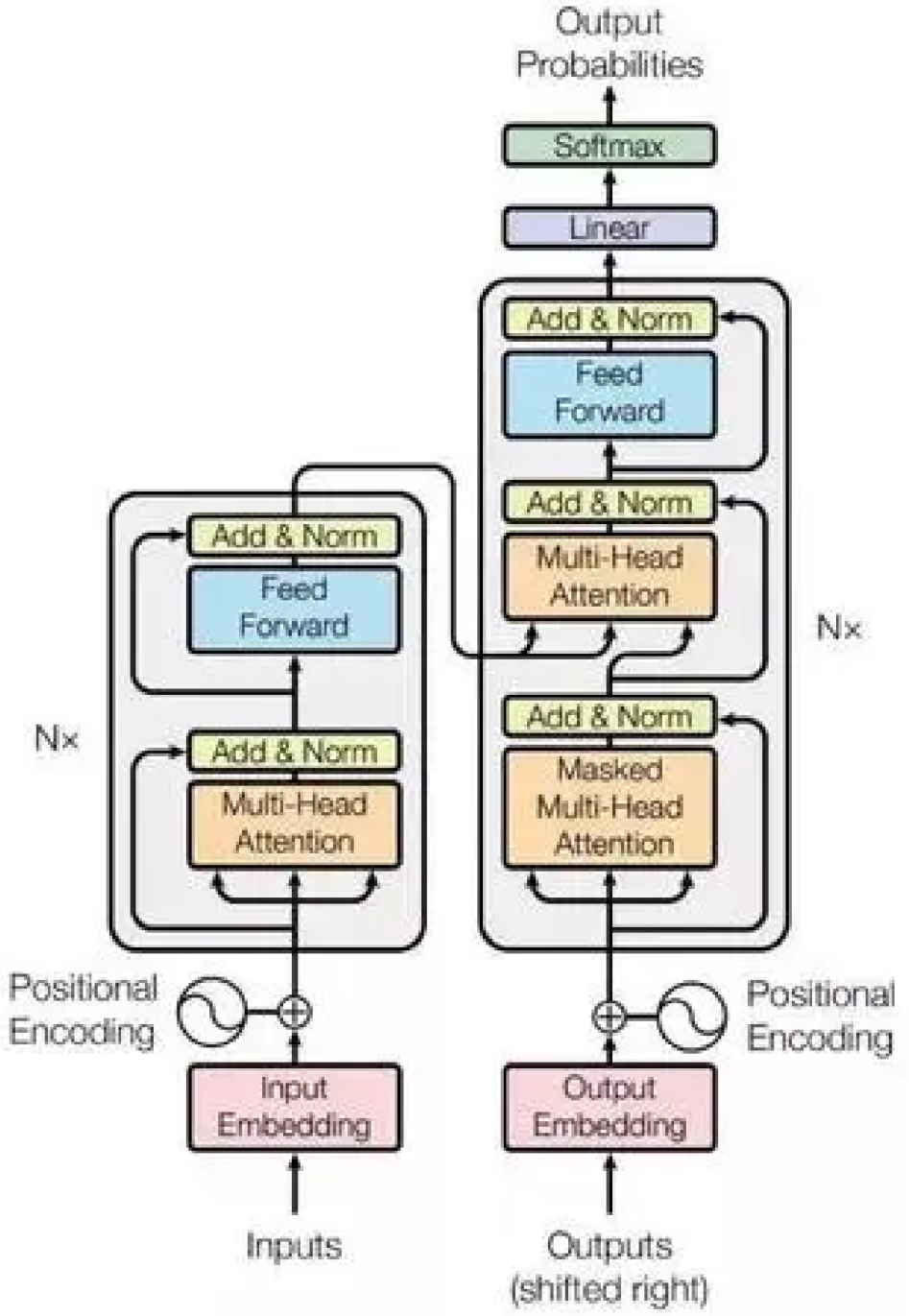
算力

- Computing Performance
- GeForce(Geometry Force) Nvida GPU



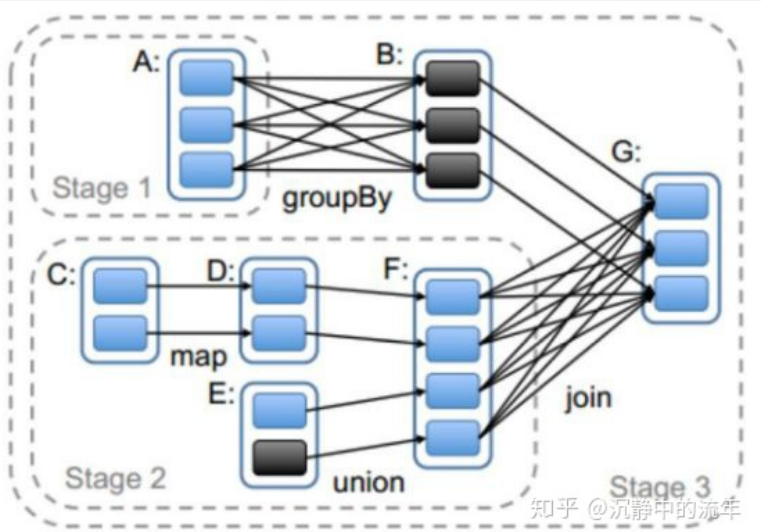
复杂问题建模

- Algebra - Geometry
- Analytic - Graphic
- Linear - Nonlinear
- Breadth - Depth



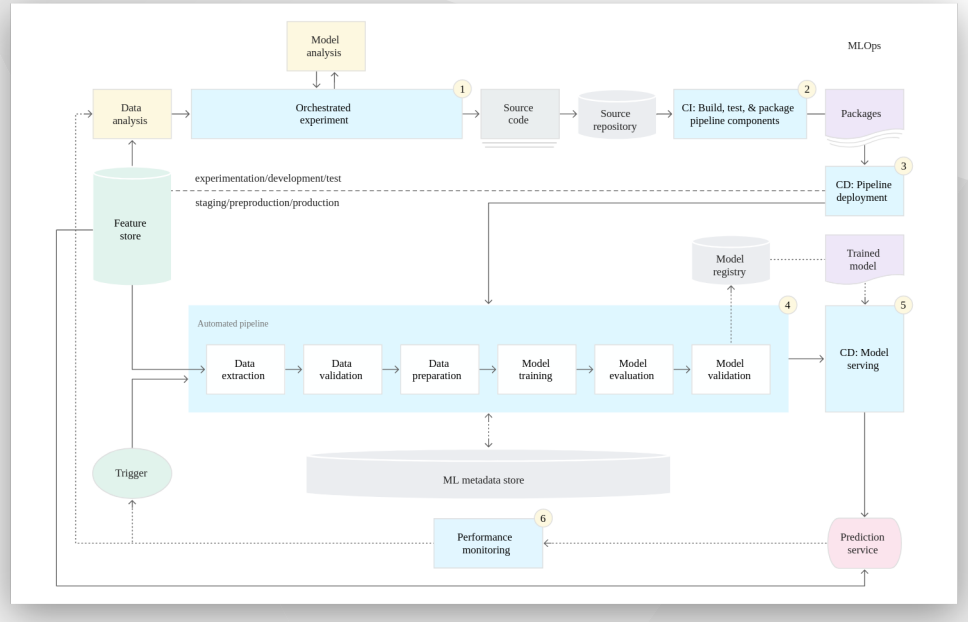
信息流与混沌

- 数据库发展
  RDBMS --> NoSQL
- 计算引擎的发展
  Map-Reduce&Resilient Distributed Dataset
- 建模与假设
  Attention is all you need
- 模型求解
  BackProp Hinton & Lecun
  Pretrain Finetune
  Stochastic Varational Inference



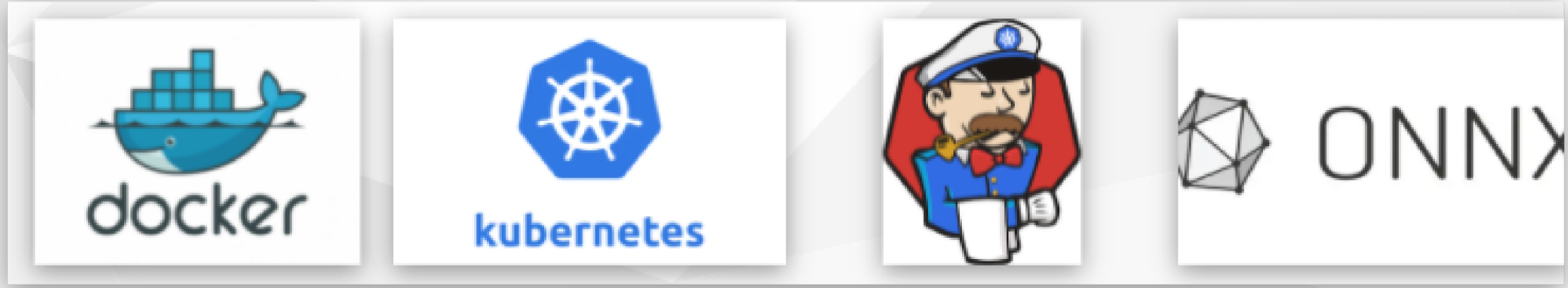
生产实际问题

- Continous Machine Learning(concept from CI&CD)
- Data Transfer Problem(Model Degeneration)
- AB-test & Gray-test（ hypothesis test & PSM-DID ）



趋势：云原生与微服务

- 容器化技术（Docker K8S）
- 美团的GPU集群出售
- Yale NLP相关的暑研(AWS)



贝叶斯方法在深度学习

- 随机项ϵ在传统统计模型的重要意义($\epsilon \perp X$)：
  - confidence interval
  - p value
- Interpretable methods in ML(Virance-Bias: Data Quality)
  - data perturbation(data augmentation)
  - model parameter randomness(random seed)
  - hyperparameter perturbation(NAS)
- Hybird: Stochastic Model + Neural Network

Stochastic Variational Inference

- Notation: oberservation x, model parameter θ latent variables z

$$p_\theta(\mathbf{x}, \mathbf{z}) = p_\theta(\mathbf{x} \mid \mathbf{z}) p_\theta(\mathbf{z})$$

- Parameter Learning Target: log evidence & Latent Posterior

$$\log p_\theta(\mathbf{x}) = \log \int d\mathbf{z} p_\theta(\mathbf{x}, \mathbf{z})$$

$$p_{\theta_{\max}}(\mathbf{z} \mid \mathbf{x}) = \frac{p_{\theta_{\max}}(\mathbf{x}, \mathbf{z})}{\int d\mathbf{z} p_{\theta_{\max}}(\mathbf{x}, \mathbf{z})}$$

SVI in Pyro cont.

- Intuition: Guide $q_\phi(\mathbf{z}) \sim p_{\theta_{\max}}(\mathbf{z} \mid \mathbf{x})$

```
def model():
    pyro.sample("z_1", ...)
def guide():
    pyro.sample("z_1", ...)
```

- Optimization Target: Evidence Lower Bound (ELBO): MM method

$$\mathrm{ELBO} \equiv \mathbb{E}_{q_\phi(\mathbf{z})}\left[\log p_\theta(\mathbf{x}, \mathbf{z}) - \log q_\phi(\mathbf{z})\right]$$

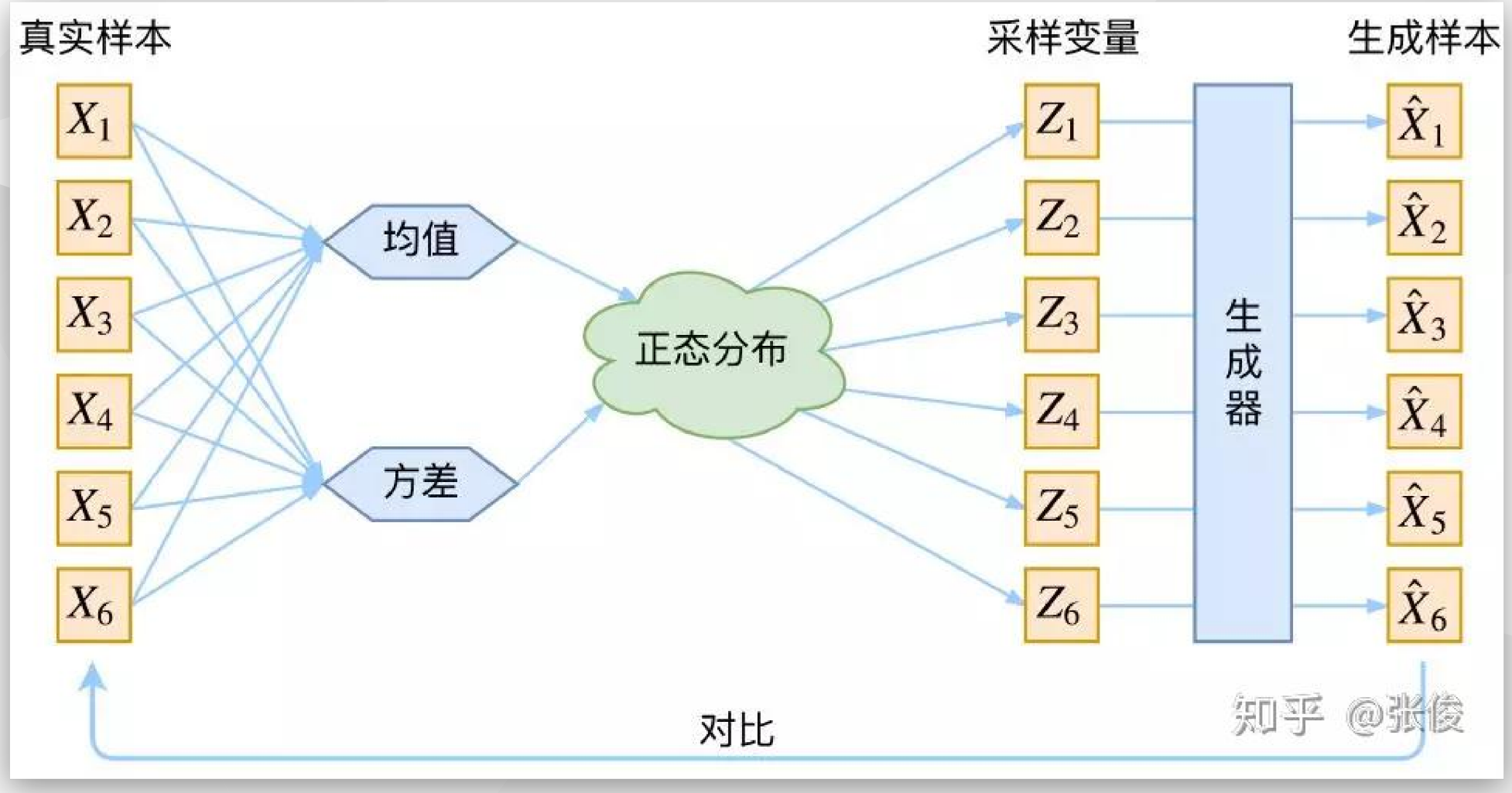
$$\log p_\theta(\mathbf{x}) - \mathrm{ELBO} = \mathrm{KL}\left(\mathrm{q}_\phi(\mathbf{z}) \| \mathrm{p}_\theta(\mathbf{z} \mid \mathbf{x})\right)$$

A Simple Example：toss the coin

```
def model(data):
    # 先验知识，正面向上的概率为 1/2
    alpha0 = torch.tensor(10.0)
    beta0 = torch.tensor(10.0)
    f = pyro.sample("latent_fairness", dist.Beta(alpha0, beta0))
    for i in range(len(data)):
        pyro.sample("obs_{}".format(i), dist.Bernoulli(f), obs=data[i])
```

```
def guide(data):
    alpha_q = pyro.param("alpha_q", torch.tensor(15.0),
                         constraint=constraints.positive)
    beta_q = pyro.param("beta_q", torch.tensor(15.0),
                        constraint=constraints.positive)
    pyro.sample("latent_fairness", dist.Beta(alpha_q, beta_q))
```

Example: Variational Auto-Encoder



```python
class VAE(nn.Module):
    def __init__(self, z_dim=50, hidden_dim=400, use_cuda=False):
        super(VAE, self).__init__()
        self.encoder = Encoder(z_dim, hidden_dim)
        self.decoder = Decoder(z_dim, hidden_dim)
        if use_cuda:
            self.cuda()
        self.use_cuda = use_cuda
        self.z_dim = z_dim
    # define the model p(x|z)p(z)
    def model(self, x):
        pyro.module("decoder", self.decoder)
        with pyro.plate("data", x.shape[0]):
            z_loc = x.new_zeros(torch.Size((x.shape[0], self.z_dim)))
            z_scale = x.new_ones(torch.Size((x.shape[0], self.z_dim)))
            z = pyro.sample("latent", dist.Normal(z_loc, z_scale).to_event(1))
            loc_img = self.decoder.forward(z)
            pyro.sample("obs", dist.Bernoulli(loc_img).to_event(1), obs=x.reshape(-1, 784))
    def guide(self, x):
        pyro.module("encoder", self.encoder)
        with pyro.plate("data", x.shape[0]):
            z_loc, z_scale = self.encoder.forward(x)
            pyro.sample("latent", dist.Normal(z_loc, z_scale).to_event(1))
    def reconstruct_img(self, x):
        z_loc, z_scale = self.encoder(x)
        z = dist.Normal(z_loc, z_scale).sample()
        loc_img = self.decoder(z)
        return loc_img
```

More Popular Stochastic Model

- Deep Generative Models
- Discrete Latent Variables
- Reinforcement Learning：Policy Gradient
- Previous Major Application
  - Time Series
  - Gaussian Processes: Kalman Filter
  - Epidemiology
  - Space Trace

Technical Trend or Hot topic

- Batch、Batch and Batch
  - More Efficient Stochastic Gradient(Dropout and Oneshot)
  - Federated Learning (Distributed)
  - Multi-Stage Transfer Learning
- Hyper、Hyper and Hyper
  - Neural Architecture Search
- Multi、Multi and Multi
  - Pretrained Model(self supervised task) and Transfer Learning
  - Multi-Source, Multi-Modal: Auto Feature Engineering

Online Reference

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http://sofasofa.io/forum_main_post.php?postid=1005437

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https://www.zhihu.com/question/264189719

Thanks