Why Aren't You Using Probabilistic Programming?

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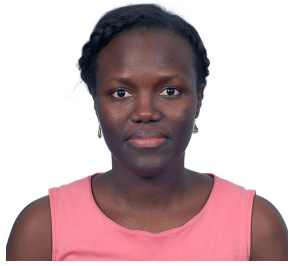

Adji Dieng

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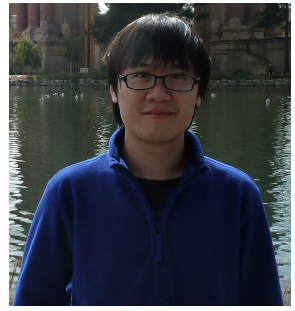

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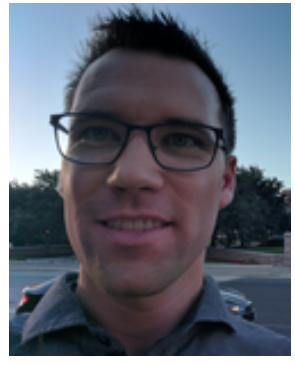

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What is probabilistic programming?

Probabilistic programs reify models from mathematics to physical objects.

- Each model is equipped with memory (“bits”, floating point, storage) and computation (“flops”, scalability, communication).

Anything you do lives in the world of probabilistic programming.

- Any computable model.
- Any computable inference algorithm.
- Any computable application.

Simulation hypothesis.

“The universe is a simulation from a computer program.”

(Zuse, Schmidhuber, Bostrom, Musk)

Inference in a probabilistic program

```
(trace, weight) = query(program, args, observations)
```

[Tenenbaum+Mansinghka NIPS 2017 tutorial]

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On Machine Learning and Programming Languages

06 Dec 2017

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carpedm20 / DCGAN-tensorflow

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A tensorflow implementation of "Deep Convolutional Generative Adversarial Networks" http://carpedm20.github.io/faces/

tensorflow dcgan gan generative-model

263 commits | 2 branches | 0 releases | 32 contributors | MIT

Branch: master | New pull request | Create new file | Upload files | Find file | Clone or dow

carpedm20 Merge pull request #208 from johnhany/Fix-filename-time ... Latest commit 251aa44 25 d

assets Rename test_***.png files 4 mon

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openai / pixel-cnn

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ython3 / Tensorflow implementation of PixelCNN++, as described in "PixelCNN++: A PixelCNN I
iscretized Logistic Mixture Likelihood and Other Modifications" https://arxiv.org/abs/1701.0551

58 commits | 3 branches | 0 releases | 5 contri

Branch: master | New pull request | Create new file | Upl

TimSalimans committed on GitHub Merge pull request #12 from prichemond/master ...

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junyanz / CycleGAN

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Software that can generate photos from paintings, turn horses into zebras, perform style transfer, and more.

computer-vision computer-graphics gan dcgan generative-adversarial-network deep-learning image-generation imag
cyclegan pix2pix

80 commits | 1 branch | 0 releases | 8 c

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junyanz Update README.md Latest comm

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openai / iaf

Unwatch

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ode for reproducing key results in the paper "Improving Variational Inference with Inverse Autoreg
tps://arxiv.org/abs/1606.04934

18 commits | 2 branches | 0 releases | 2 contribu

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dpkingma Merge pull request #12 from openai/revert-8-tf_utils_bugfix ...

graphy .

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hanzhanggit / StackGAN

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Code | Issues 21 | Pull requests 0 | Projects 0 | Wiki | Insights

No description, website, or topics provided.

13 commits | 1 branch | 0 releases | 1 contributor

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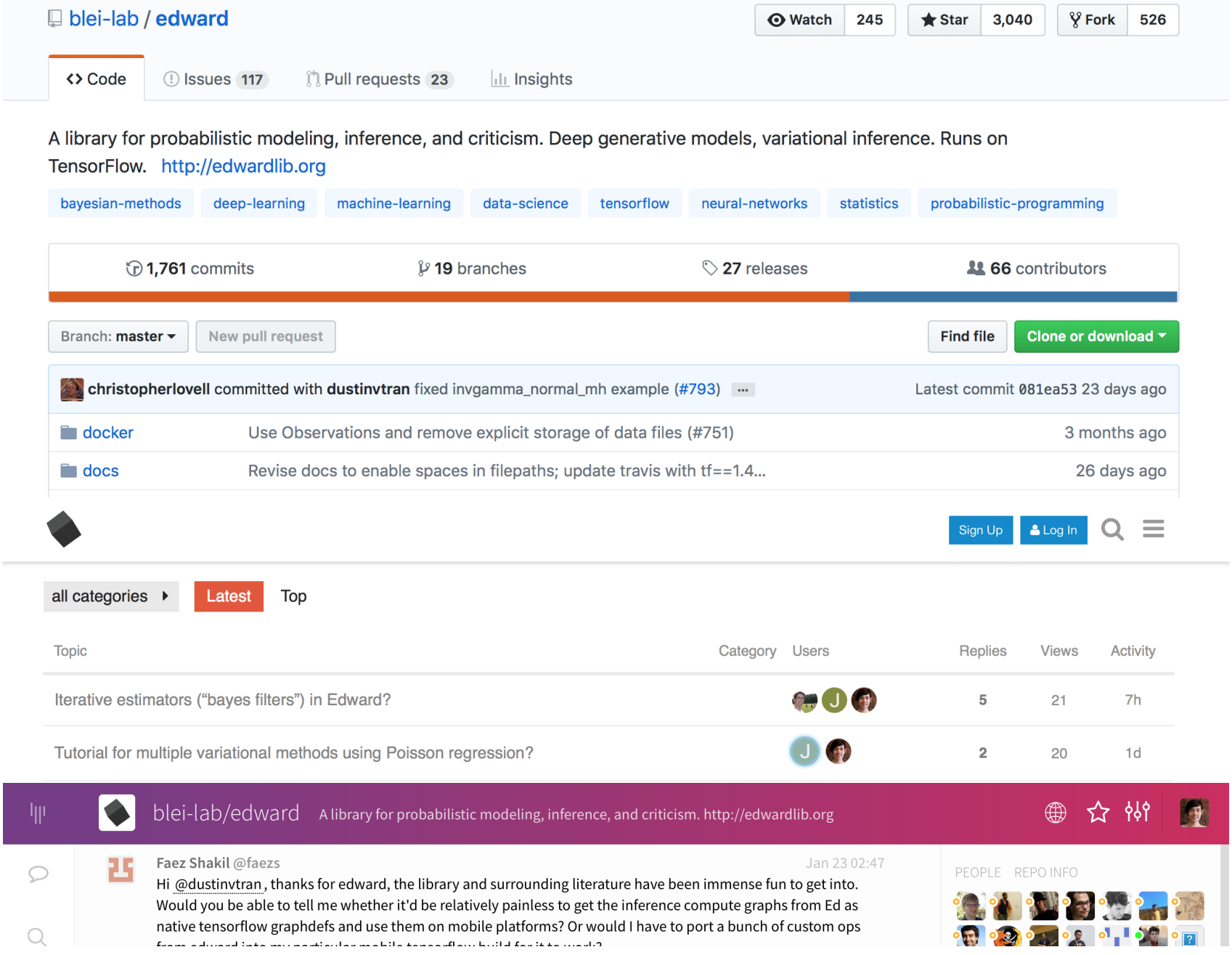
Data first commit

demo first commit

The Myth of Probabilistic Programming

Programming is infeasible if a core operation in the language is NP-hard.

For high-dimensional problems + modern probabilistic models, we haven't solved automated inference.



We have an active community of several thousand users & many contributors.

Language: Computational Graphs w/ Random Variables

Edward's language augments computational graphs with an abstraction for random variables. Each random variable **x** is associated to a tensor $\mathbf{x}^*$, $\mathbf{x}^* \sim p(\mathbf{x} \mid \theta^*)$.

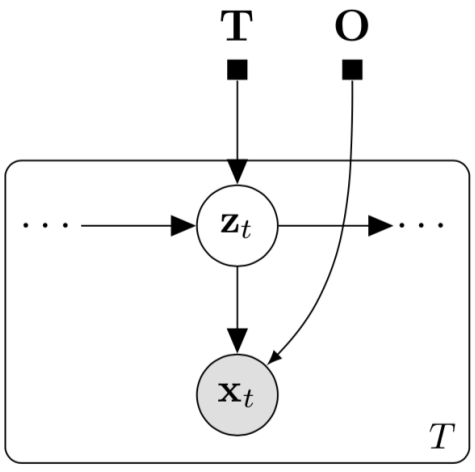
```
# univariate normal
Normal(loc=0.0, scale=1.0)
# vector of 5 univariate normals
Normal(loc=tf.zeros(5), scale=tf.ones(5))
# 2 x 3 matrix of Exponentials
Exponential(rate=tf.ones([2, 3]))
```

Unlike `tf.Tensors`, `ed.RandomVariables` carry an explicit density with methods such as `log_prob()` and `sample()`.

For implementation, we wrap all TensorFlow Distributions and call `sample` to produce the associated tensor.

[Tran+ 2017]

Language Example



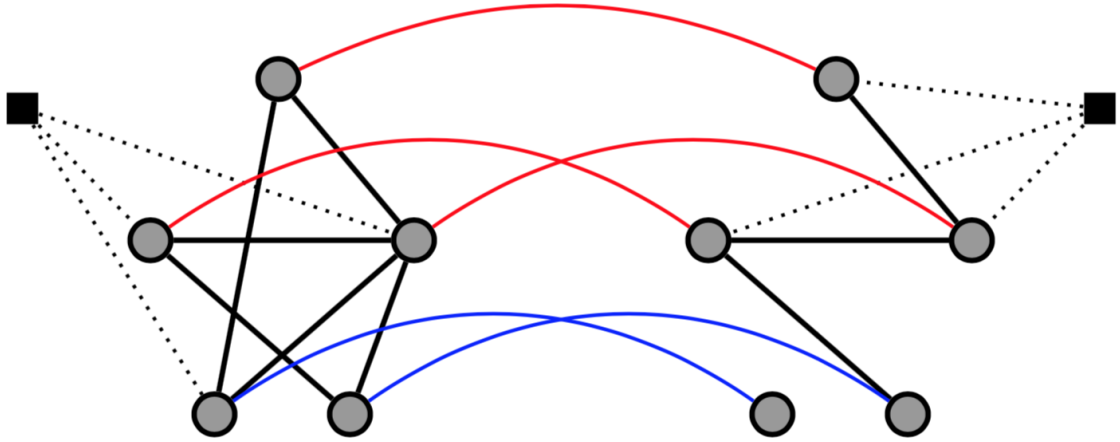

```
1  from edward.models import Normal
2
3  T = tf.Variable(tf.random_normal([K, K]))
4  O = tf.Variable(tf.random_normal([K, D]))
5  z = x = []
6  z[0] = Normal(loc=tf.zeros(K), scale=tf.ones(K))
7  x[0] = Normal(loc=tf.matmul(z[0], O), scale=0.5)
8  for t in range(1, T):
9    z[t] = Normal(loc=tf.matmul(z[t - 1], T), scale=0.1)
10   x[t] = Normal(loc=tf.matmul(z[t], O), scale=0.5)
```

State space model for sequences $\mathbf{x} = [\mathbf{x}_1, \ldots, \mathbf{x}_T] \in \mathbb{R}^{T \times D}$.

Edward's language enables a *calculus* on random variables.

[Dillon+ 2017]

Inference as Stochastic Graph Optimization



All `Inference` has (at least) two inputs:

1. red aligns latent variables and posterior approximations;
2. blue aligns observed variables and realizations.

```
inference = ed.Inference({beta: qbeta, z: qz}, data={x: x_train})
```

`Inference` has class methods to finely control the algorithm. Edward is as fast as handwritten TensorFlow at runtime.

edwardlib.org/api

Composable & Hybrid Inference

```
n_samples = n_iter_per_epoch * n_epoch
qz = Empirical(tf.Variable(tf.random_normal([n_samples, mnist.train.size, K])))

inference_e = ed.SGHMC({z: qz}, data={x: x_train})
inference_e.initialize()

inference_m = ed.MAP(data={x: x_train, z: qz.params[inference_e.t]})
optimizer = tf.train.RMSPropOptimizer(1e-2, epsilon=1.0)
inference_m.initialize(optimizer=optimizer)
```

```
inference_z1 = ed.KLpq({beta: qbeta, z1: qz1}, {x1: x1_train})
inference_z2 = ed.KLpq({beta: qbeta, z2: qz2}, {x2: x2_train})
...
for _ in range(10000):
  inference_z1.update()
  inference_z2.update()
```

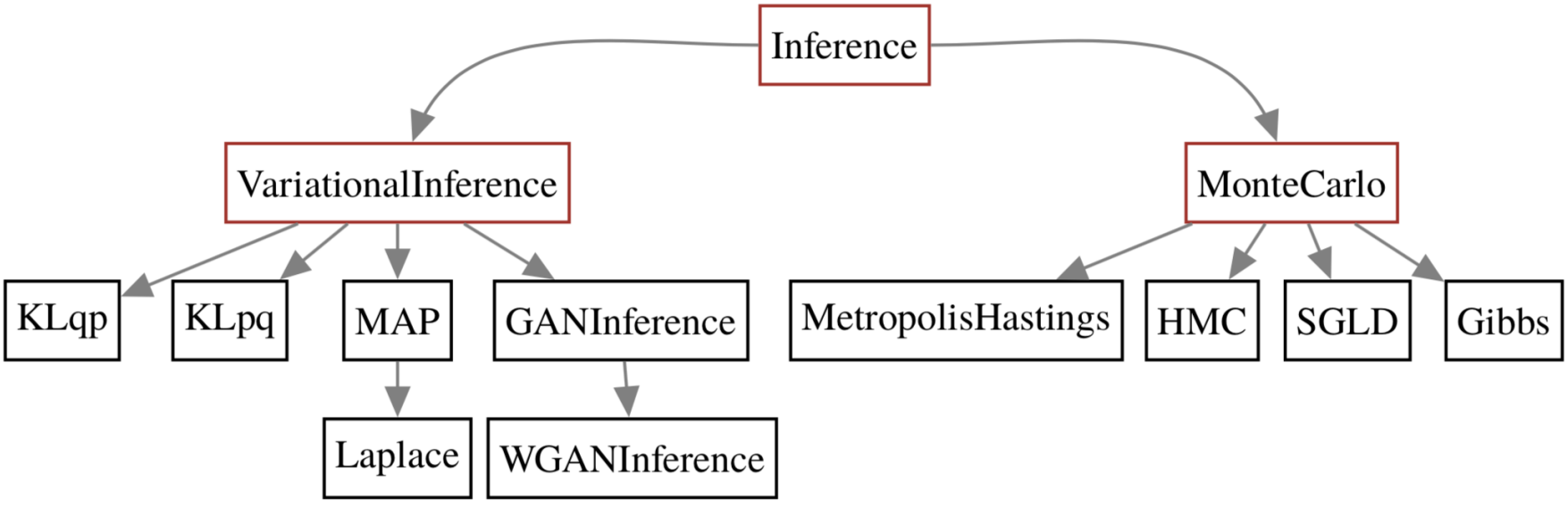
[Hoffman 2017; Tran 2017; etc.]

Non-Bayesian Inference

```
def generative_network(eps):
  h = Dense(256, activation='relu')(eps)
  return Dense(28 * 28, activation=None)(h)

def discriminative_network(x):
  h = Dense(28 * 28, activation='relu')(x)
  return Dense(h, activation=None)(1)

# Probabilistic model
eps = Normal(loc=tf.zeros([N, d]), scale=tf.ones([N, d]))
x = generative_network(eps)

inference = ed.GANInference(data={x: x_train},
    discriminator=discriminative_network)
inference.run()
```

[Dayan+ 1995; Gutmann+ 2010]

Taxonomy of Inference



Nodes are Edward classes. Arrows denote inheritance.

edwardlib.org/api

Why You Shouldn't Use Probabilistic Programming

- **Object-oriented inference** has a high cognitive burden.
- Sometimes it's easier to **build the loss function** than it is to build the program. (e.g. autoregressive models)
- **Programmable inference is hard**. Matt and I spent a year on covering use cases. But we didn't cover all of them.

Why You Will Use Probabilistic Programming

Distributed, Compiled, Accelerated Systems

Probabilistic programming over multiple machines. XLA compiler optimization and TPUs. More flexible programmable inference.

Dynamic Graphs

PROB TORCH

Probabilistic Torch is library for deep generative models that extends PyTorch. It is similar in spirit and design goals to Edward and Pyro, sharing many design characteristics with the latter.

The design of Probabilistic Torch is intended to be as PyTorch-like as possible. Probabilistic Torch models are written just like you would write any PyTorch model, but make use of three additional constructs:

Distributions Backend

```
def pixelcnn_dist(params, x_shape=(32, 32, 3)):
  def _logit_func(features):
    # single autoregressive step on observed features
    logits = pixelcnn(features)
    return logits
  logit_template = tf.make_template("pixelcnn", _logit_func)
  make_dist = lambda x: tfd.Independent(tfd.Bernoulli(logit_template(x)))
  return tfd.Autoregressive(make_dist, tf.reduce_prod(x_shape))

x = pixelcnn_dist()
loss = -tf.reduce_sum(x.log_prob(images))
train = tf.train.AdamOptimizer().minimize(loss)  # run for training
generate = x.sample()  # run for generation
```

TensorFlow Distributions consists of a large collection of distributions. `Bijector` enable efficient, composable manipulation of probability distributions.

Pytorch PPLs are consolidating on a backend for distributions.

[Dillon+ 2017]

References

edwardlib.org

- Edward: A library for probabilistic modeling, inference, and criticism.
  arXiv preprint arXiv:1610.09787, 2016.
- Deep probabilistic programming.
  International Conference on Learning Representations, 2017.
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