A Machine Learning Approach to Routing

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Premise

- 2017 – ML still hasn't been properly explored for networking
- Goal: Preliminary work exploring ML for routing
- Lots of past work on flow optimisation – for given topology and traffic demands, optimal routing configurations can be computed
  - Fail miserably in dynamic situations
    - Given past traffic conditions, optimise with respect to them and hope it works well in the future
    - Find a good (static) routing configuration for a range of traffic scenarios

High Level Questions

- Learn next input (“demand”) then calculate routing, or learn routing configuration directly?
- What should a learning algorithm produce?
- Will supervised learning work?
- Can we use reinforcement learning?

Model

- Goal: repeatedly select routing configuration minimizing congestion
- Model network as a directed graph where edge weights are link capacities
- *Routing Strategy*: for all source s and destination d pairs, at any vertex v, how traffic going from s to t through v is split across neighbors of v
  - $|V|^2 * |E|$ variables overall
  - Require loop-free routing
- *Demand Matrix:* specifies traffic demand between all (source, destination) pairs

Stategies

- Given a demand matrix D, we can calculate an optimal routing strategy via linear programming
- Supervised Learning
  - Predict next demand matrix, given past D's
  - Calculate routing strategy from result
- Reinforcement Learning
  - Learn routing strategy directly from sequence of last k D's

Supervised Learning

- Assume regularity in network demand (daily, weekly cycles etc)
- Input: last *k* demand matrices, predict next D
- Various neural nets: fully connected; CNN; NAR-NN (nonlinear auto-regressive)
- Generate “actual” demand matrix sequences
  1) Deterministically generated from prior D's (cyclic of length q)
  2) Independently generated from fixed prob dist.
- Result: only NAR-NN succeeds for only cyclic scenario if $q < k$

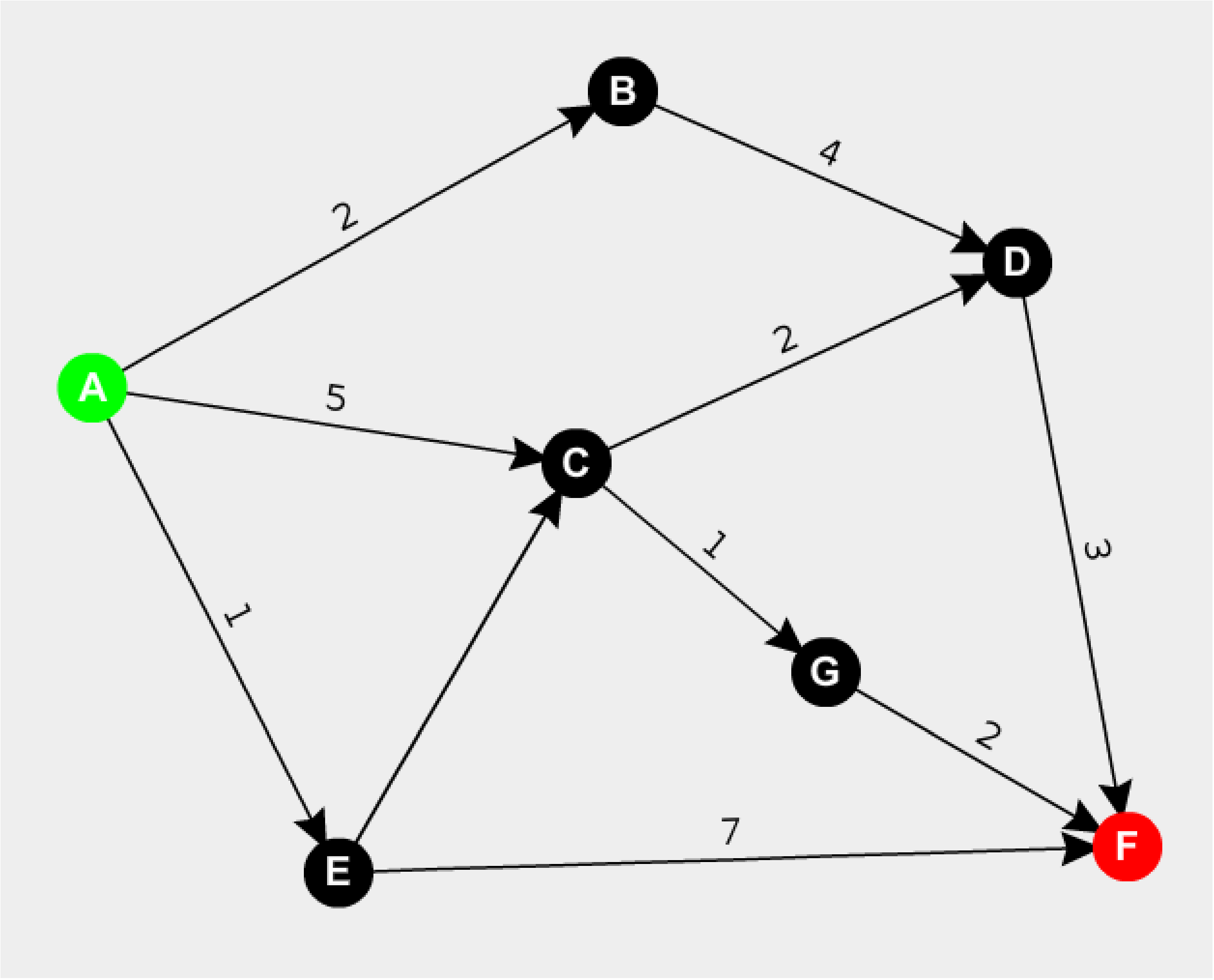
Reinforcement Learning

- $|V|^2*|E|$ is too large
- Destination-based routing: each vertex splits traffic across neighbors based only on destination: $|V|*|E|$
- TRPO [4] learning on 3 layer, fully connected NN
- Reward = (*max-link-utilization* / *optimal-max-link-utilization)* given the next real D
- Learn mapping from k past D's to per-vertex traffic splitting ratios (*softmax*(real output) → routing probabilities)
- Result: 700 epochs, still produces high *max-link utilization*
- Authors propose number of output parameters is too large

Reinforcement Learning – Softmin Routing

- Only learn 1 parameter per edge: |E| parameters
- Given parameters p, and vertex v, we can calculate edge weights via shortest-path intermediate step, then apply *softmin* to calculate splitting probabilities
- Reward same as before
- Compare to three baselines: softmin routing based directly on prior D, based on average of last D's, and oblivious [3] (routing strategy independent of past D's)

$$softmin_\gamma(\alpha)_i = \frac{e^{-\gamma\alpha_i}}{\sum_{j=1}^{r}(e^{-\gamma\alpha_j})}$$



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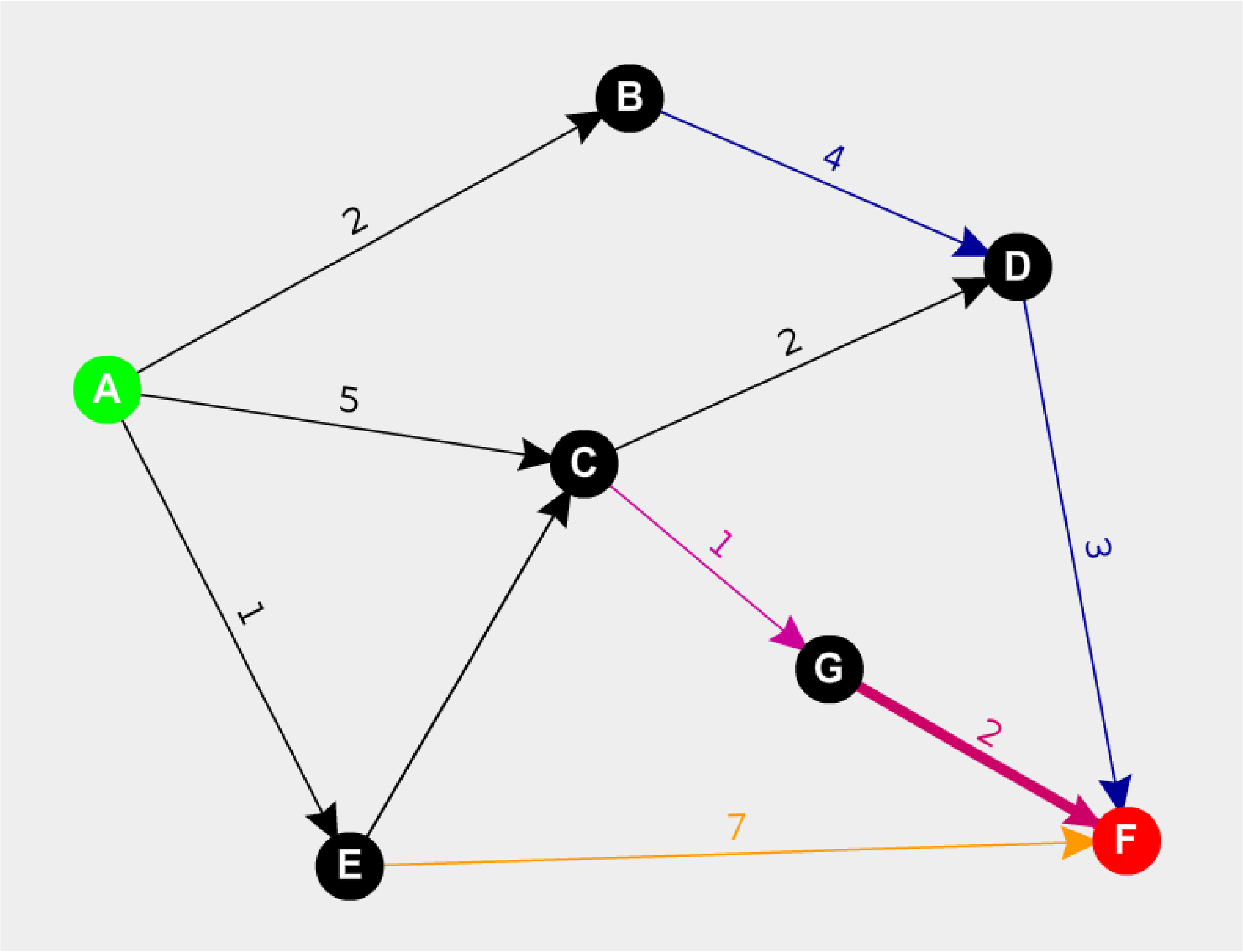
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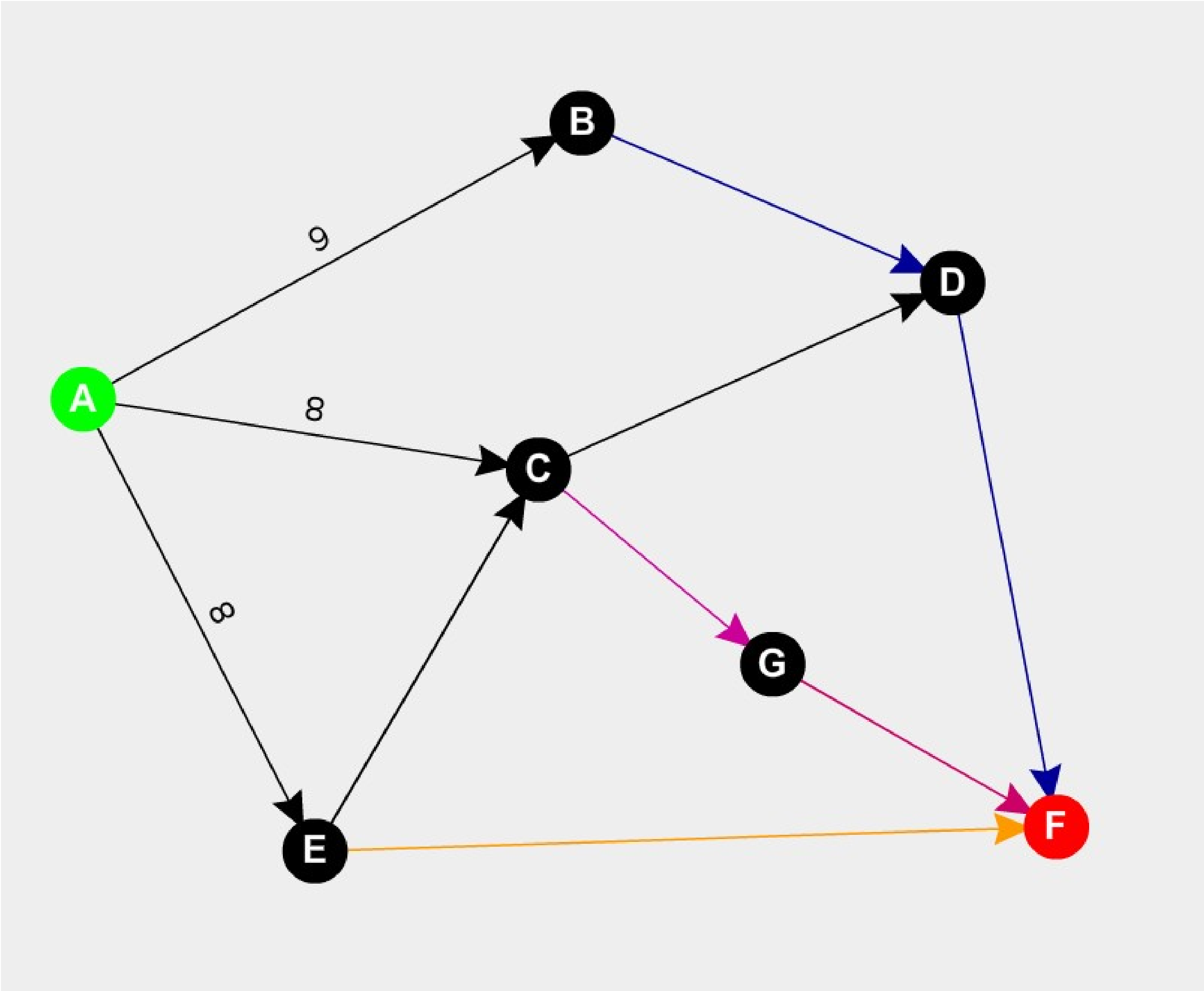

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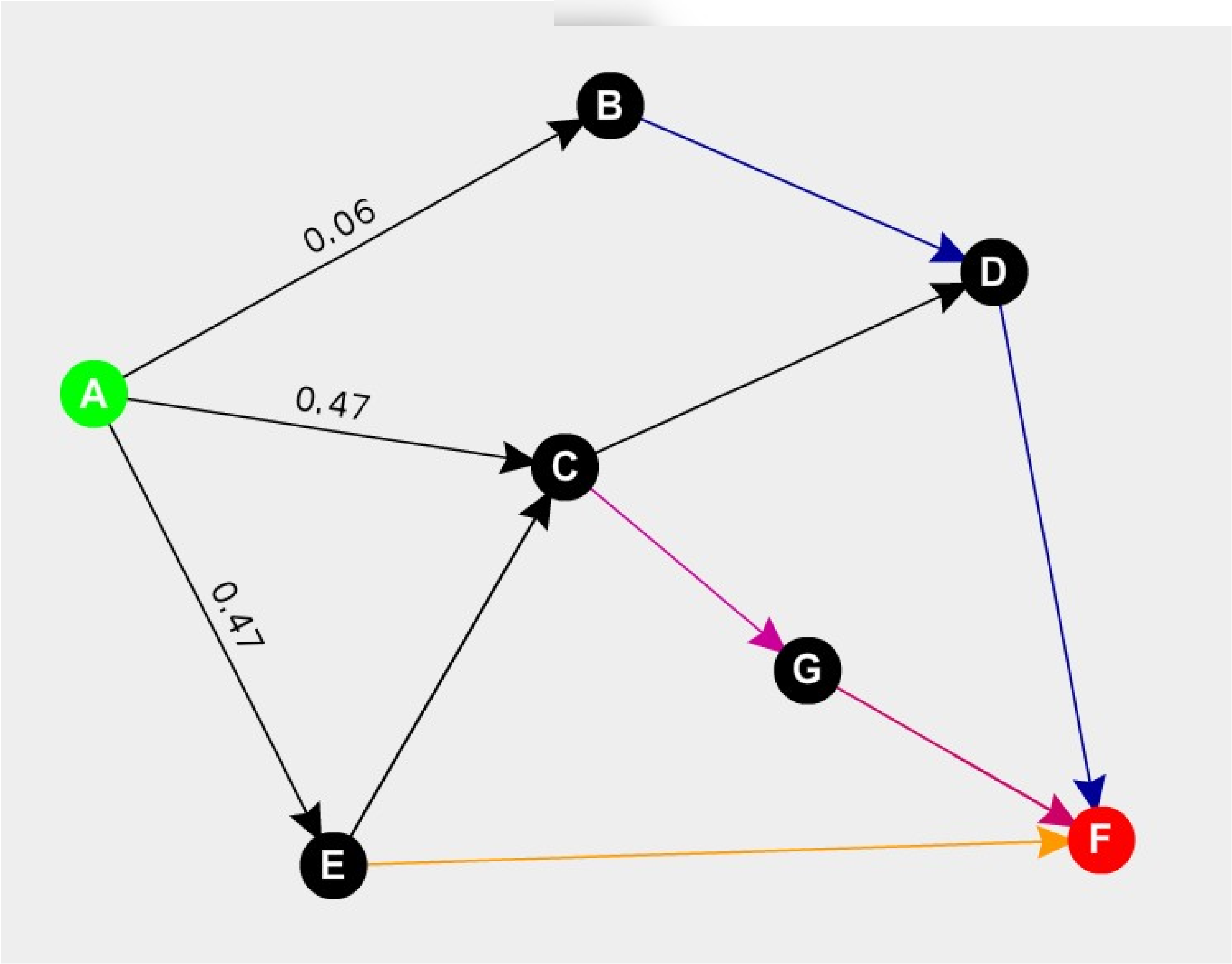
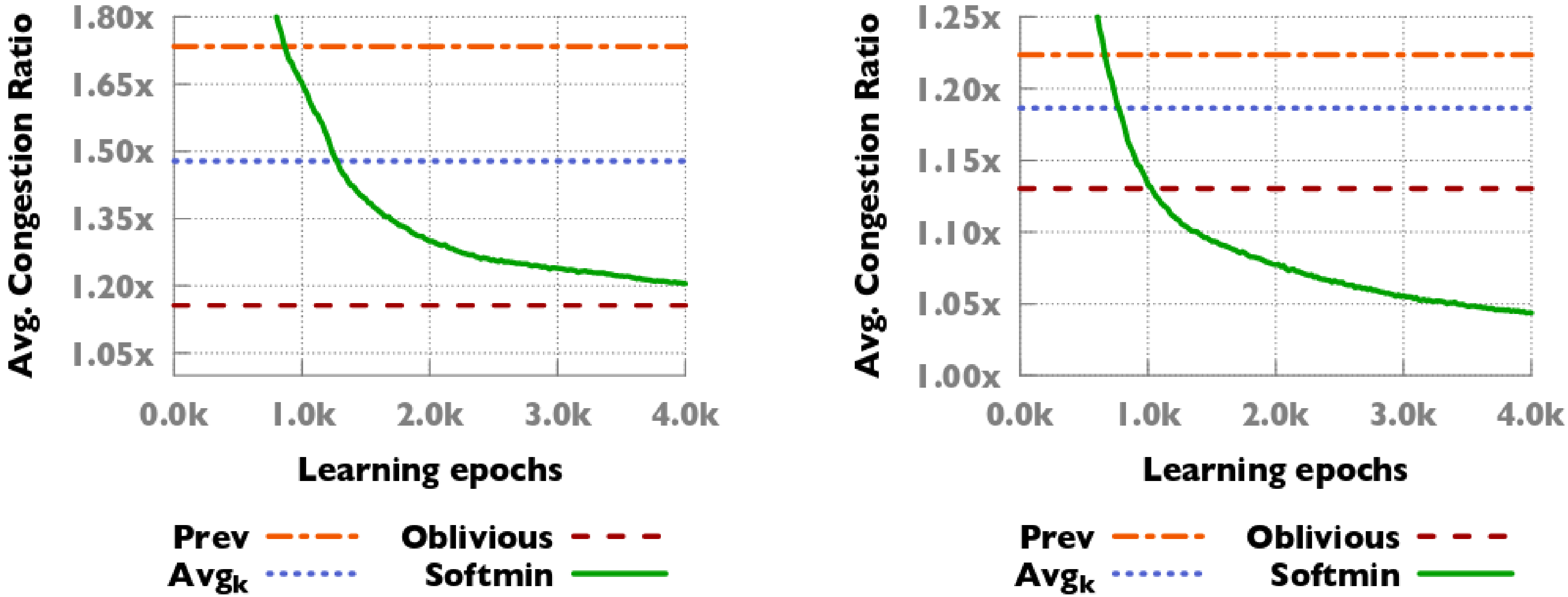
$$softmin_{\gamma}(\alpha)_i = \frac{e^{-\gamma \alpha_i}}{\sum_{j=1}^{r}(e^{-\gamma \alpha_j})}$$



It works!



(a) *Congestion ratio for sparse ($p = 0.3$) gravity DM sequences*

(b) *Congestion ratio for bimodal DM sequences with 40% elephant flows*

Figure 2: *Representative Results for $softmin$-Routing*

Discussion

- Claims to be a very early paper in ML applied to routing
  - Very broad, shallow analysis
  - Not much evaluation presented except for select cases
  - Try to cover a huge configuration space: different ways to generating individual demand matrices, sequences of matrices, neural net architectures, supervised/reinforcement...
- There have been starts at using learning in networking in the 90s [2]
- Only recently a few papers published with modern ML techniques

Discussion

- Could spawn lots of future work
  - Different types of networks (including less simplified models)
  - More training time, different architectures (RNN?)
  - Different supervised learning approaches
- Big Idea
  - ML has lots of potential for generating efficient, dynamic routing strategies

References

1) A. Valadarsky et al.: A Machine Learning Approach to Routing, arXiv, 2017.
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