Machine Learning on Flink

Ted Dunning
MapR Technologies

Machine Learning on Flink (without Flink ML)

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*well, with Flink ML if desired, but not just with Flink ML

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Where to Today?

- What is important in machine learning systems?
- What isn't like it seems?
- What can I/we/you do to improve it?

Traditional View

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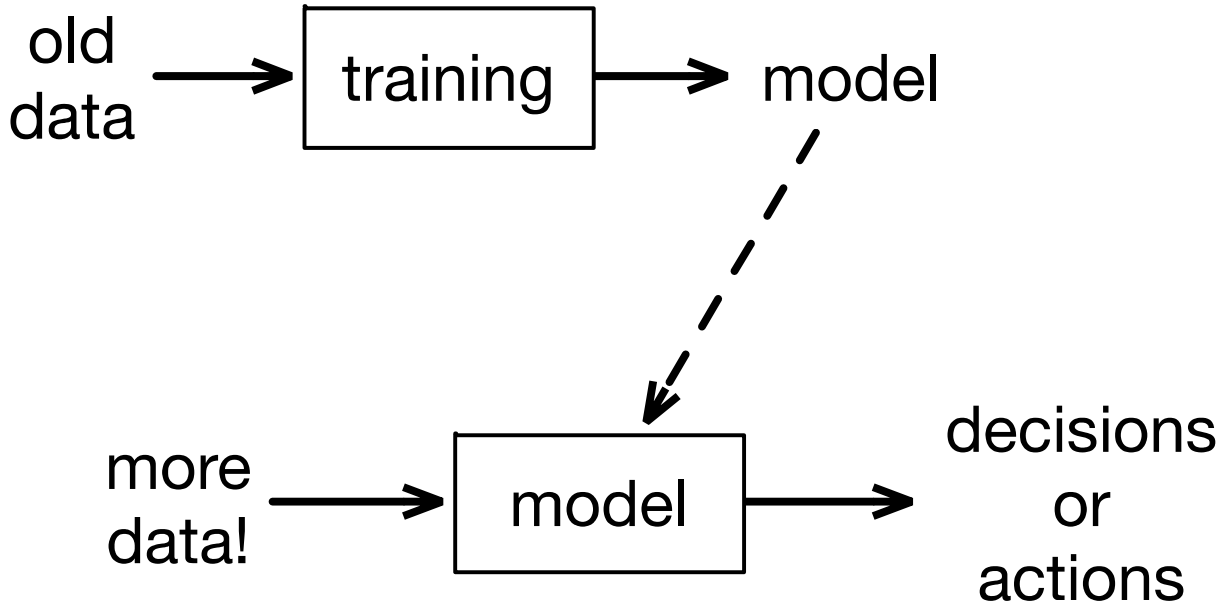


Not so much!

90+% of effort is logistics, not learning

Why Not?

- Just getting the training data is hard
  - Bootstrap problem for first models
  - First models and later can record input data
  - New kinds of observations force restarts
  - Requires a ton of domain knowledge

- The myth of the unitary model
  - You can’t train just one
  - You will have dozens of models, likely hundreds to thousands
  - Handoff to new versions is tricky

Why Not? (continued)

- Recording raw-ish data is really a ***big*** deal
  - Data as seen by a model is worth gold
  - Data reconstructed later often has time-machine leaks
  - Databases were made for updates, streams are safer

- Real validation can be hard and takes time
  - Especially true if models effectively pick their own training data
  - Consider model over-ride for interesting data
  - Reject inference can be very difficult without a good framework
  - Thompson sampling can provide (near) optimal solution

How to Do Better … Spoilers

- It's the data!
- Prioritize – put serious effort into infrastructure
- Persist – use streams to keep data around
- Measure – everything, and record it
- Meta-analyze – understand and see what is happening
- Containerize – make deployment repeatable, easy

- Oh… don't forget to do some machine learning, too

How to Do Better – Big Picture

- The biggest improvements probably aren't machine learning
  - Algorithms are fun, but probably not the biggest bang

- Acquiring better data can make massive difference
  - Example: Clicks versus 30 second views
- Asking a better question can make massive difference
  - Example: When does new stock arrive versus stock recommender

- The 17th model revision will probably make <1% difference
- Consider $/minute of effort, invest wisely

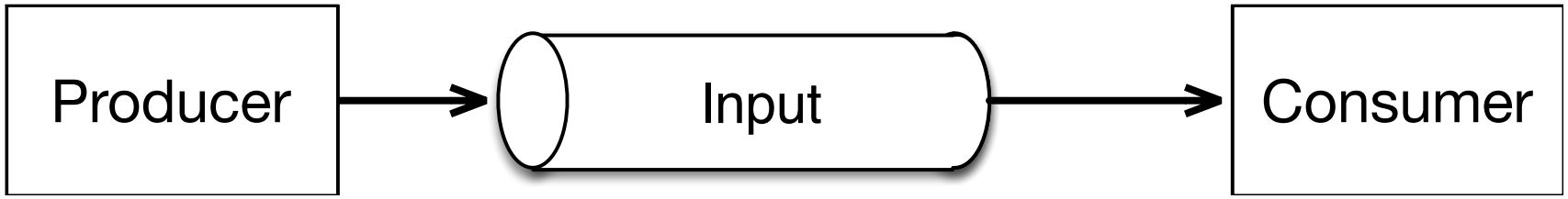
How to Do Better – Data and Deployment

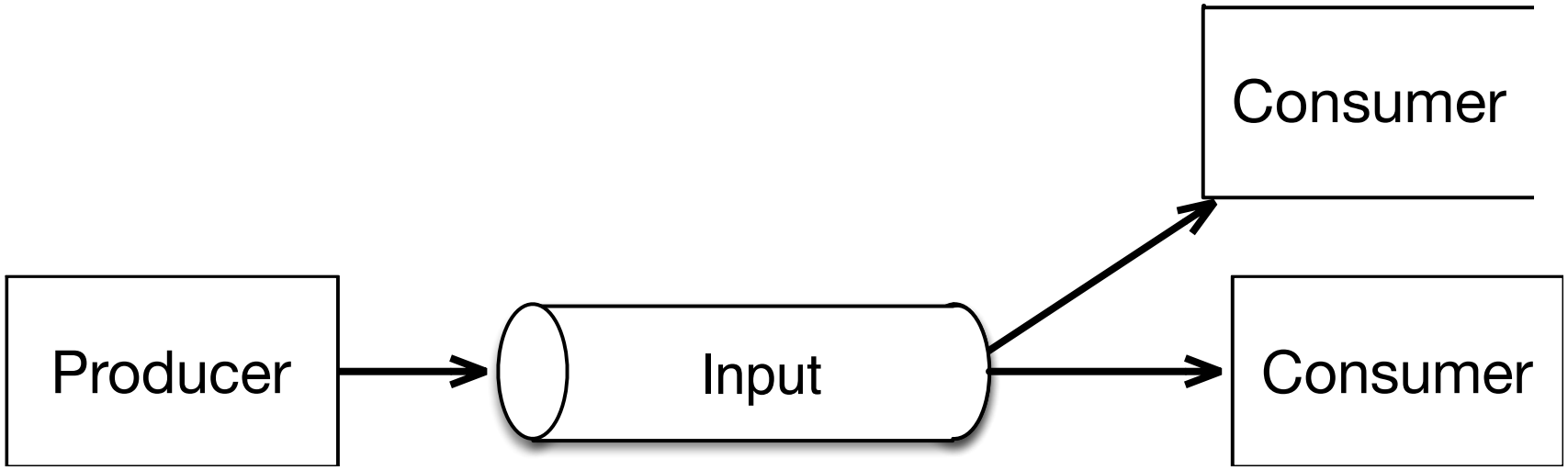
- Deploy a decoy model
  - Looks like a server, but it just archives inputs
  - Safe in a good streaming environment, less safe without good isolation

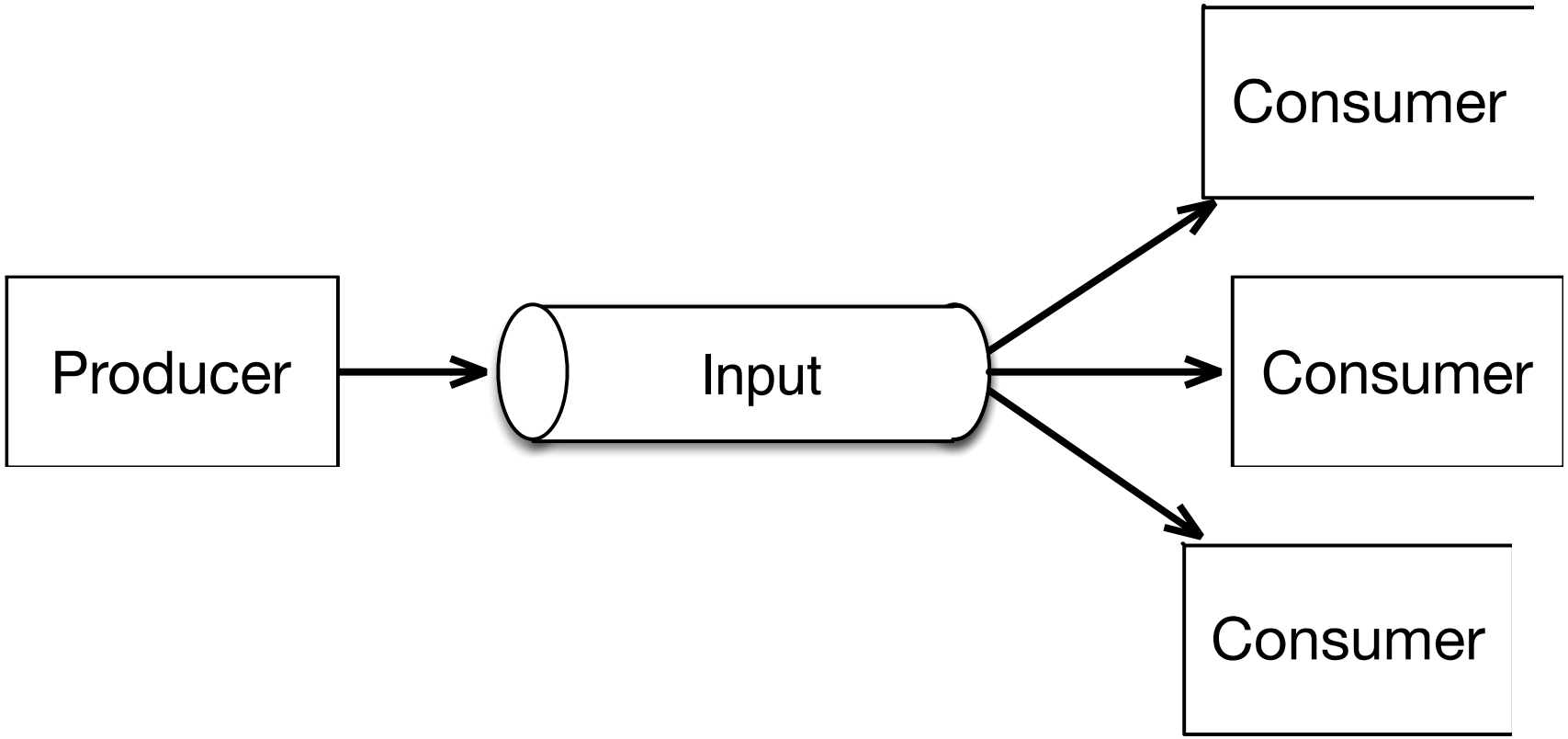
- Deploy a canary server
  - Keep an old model active as a reference
  - If it was 90% correct, difference with any better model should be small
  - Score distribution should be roughly constant
  - Many things can disturb the canary, but if it is stable, things are likely OK

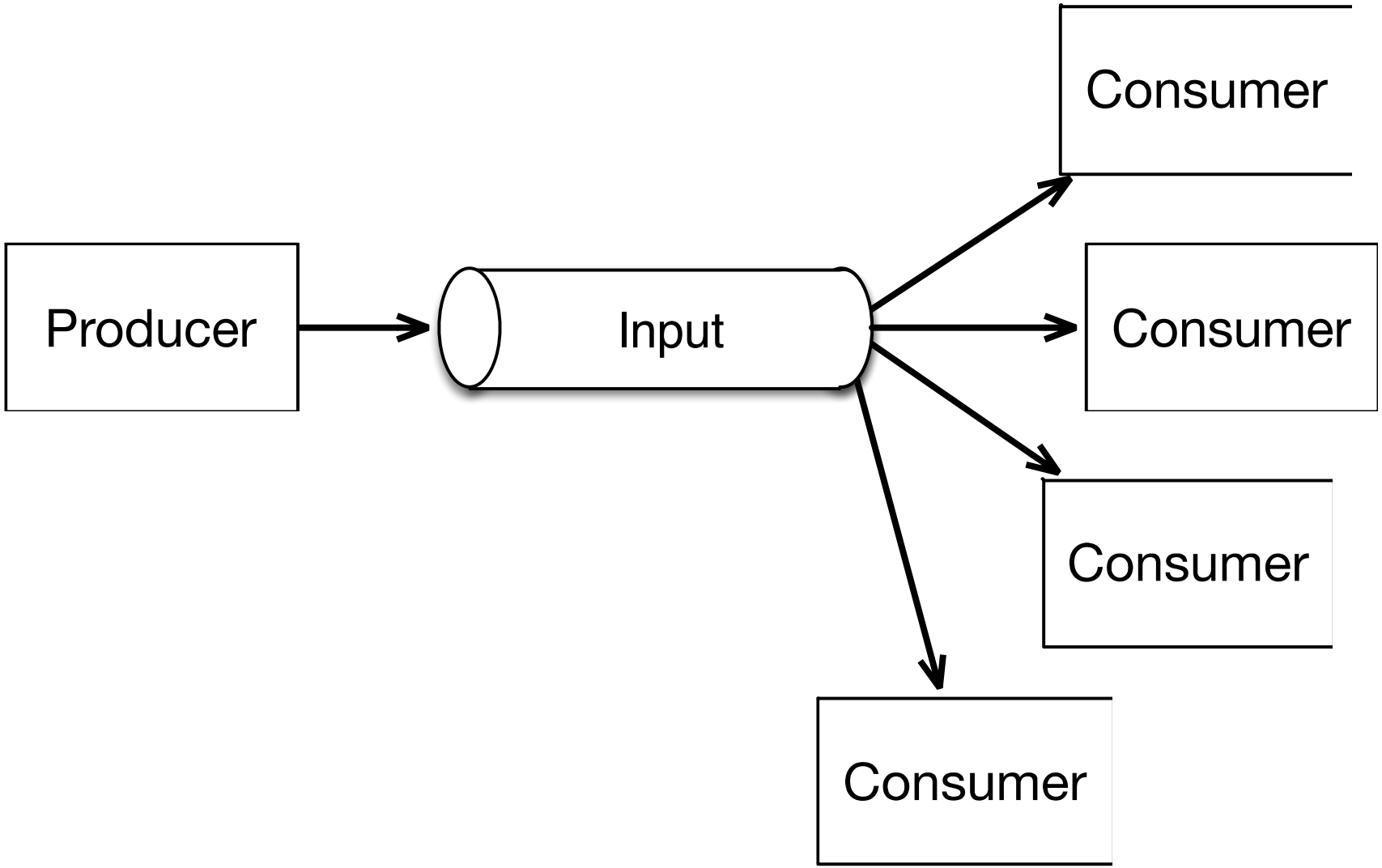
A decoy and a canary walked into a bar and asked for a bottle of Club Maté..

Bartender said, “Wouldn’t you rather have a stream?”









Features of Good Streaming

- It is Persistent
  - Messages stick around for other consumers
  - Consumers don't affect producers

- It is Performant
  - You don't have to worry if a stream can keep up

- It is Pervasive
  - It is there whenever you need it, no need to deploy anything
  - How much work is it to create a new file? Why harder for a stream?

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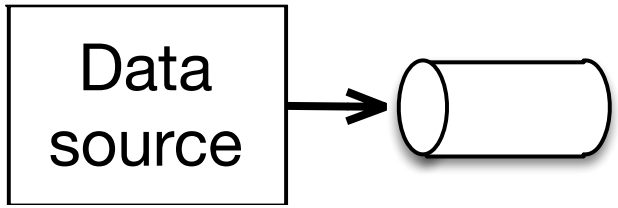
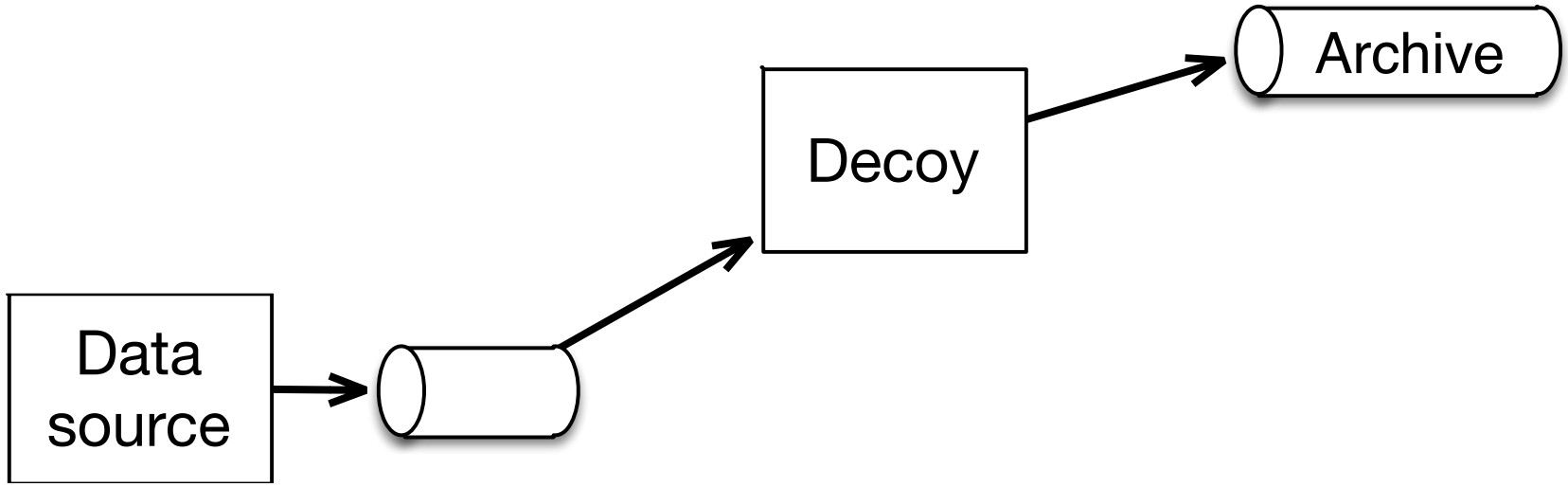
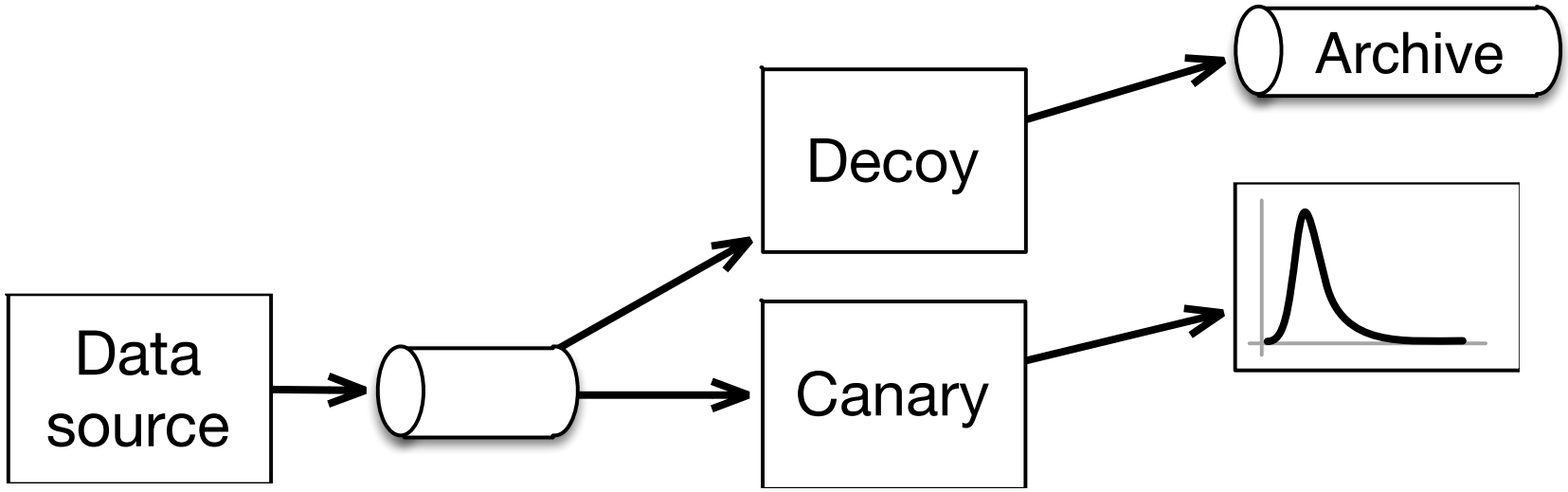
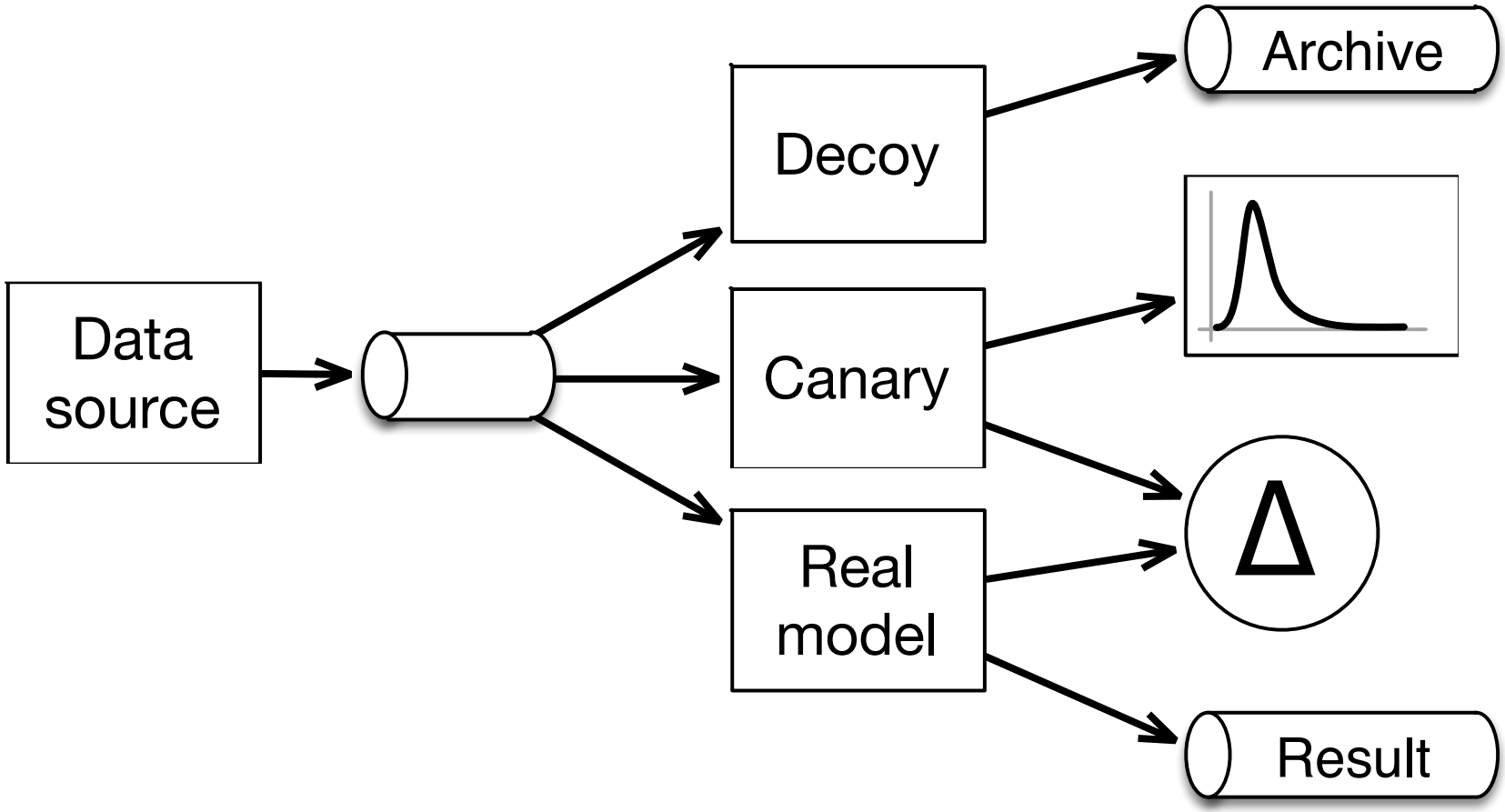


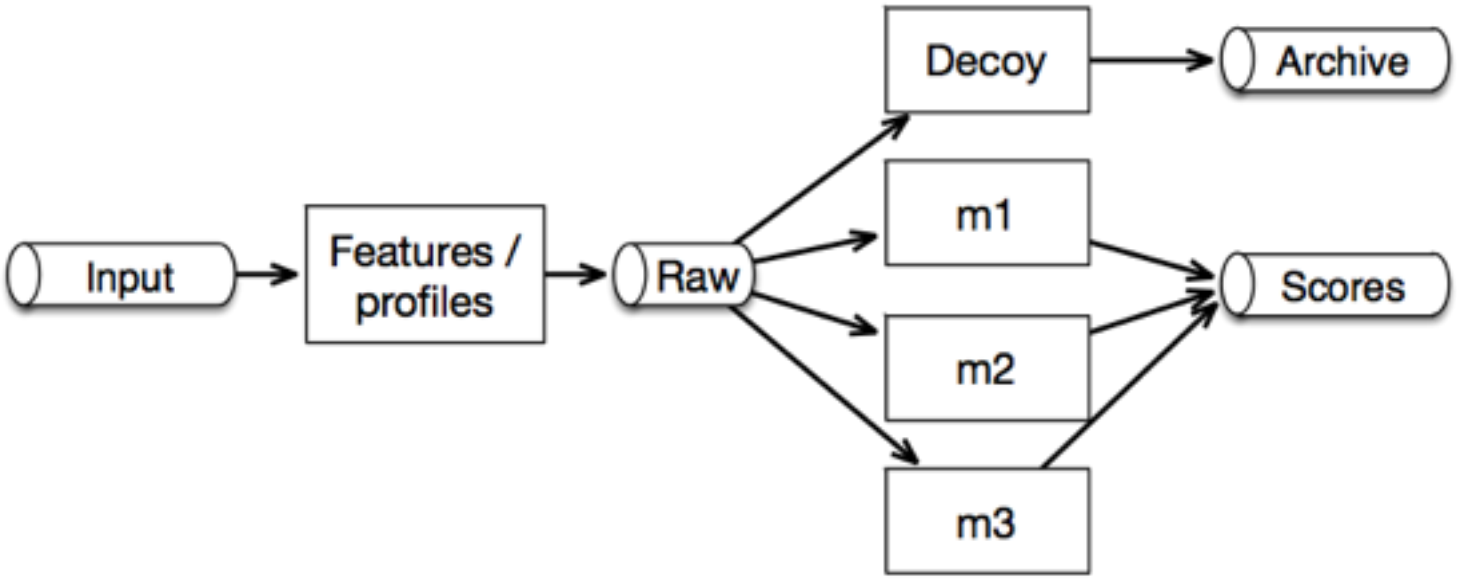






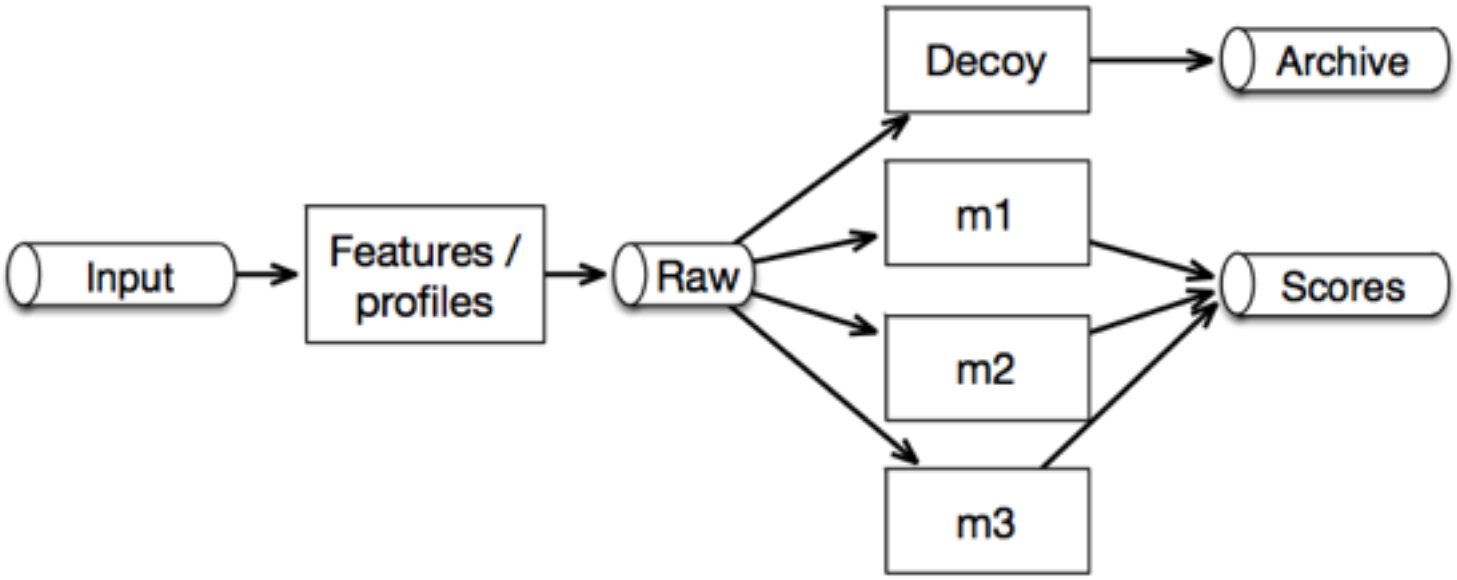
How to Do Better – Containers and Rendezvous

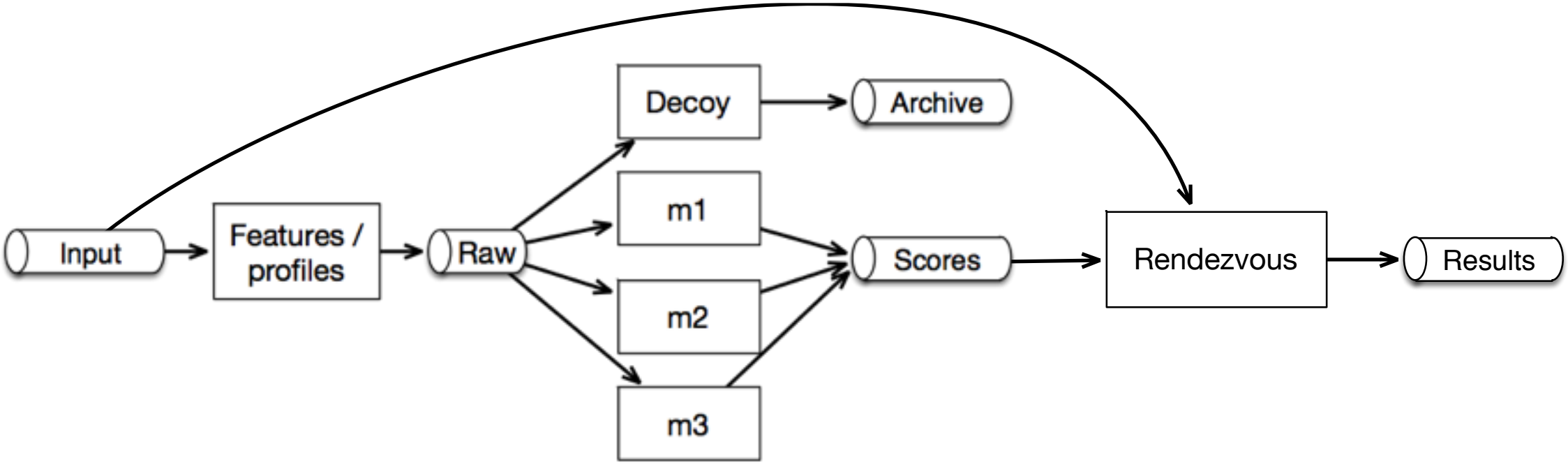
- Containerize all models
  - Safe deployment
  - Take input from stream
  - Write output to stream
  - Annotate output with meta-data about who, what and when
  - Pre-rig for standard operations like metrics, timing, annotation

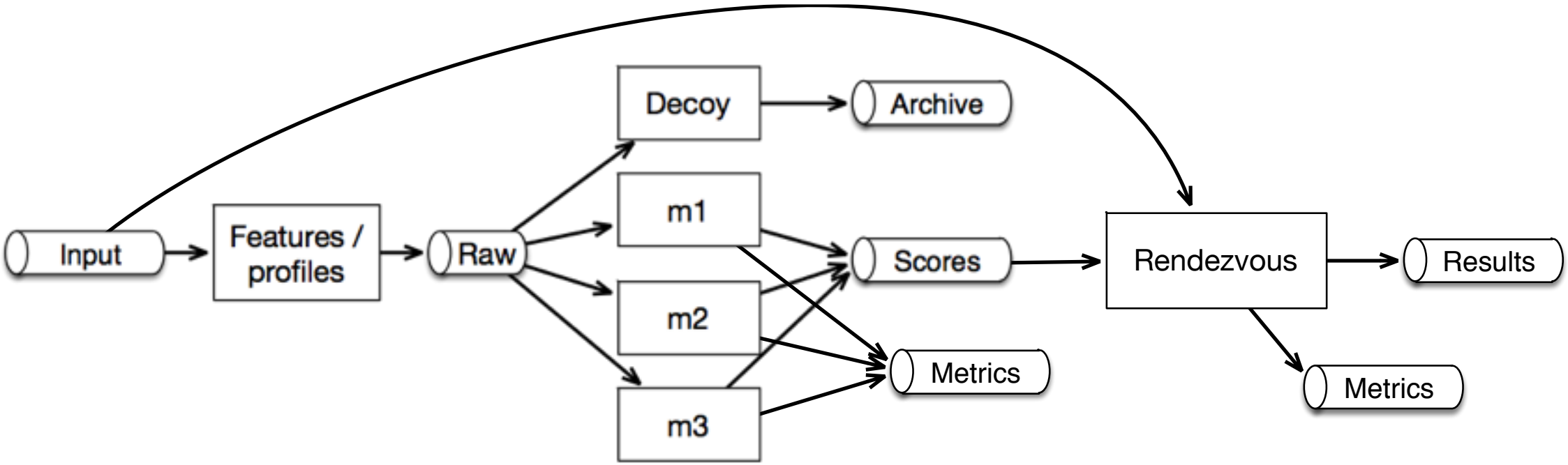


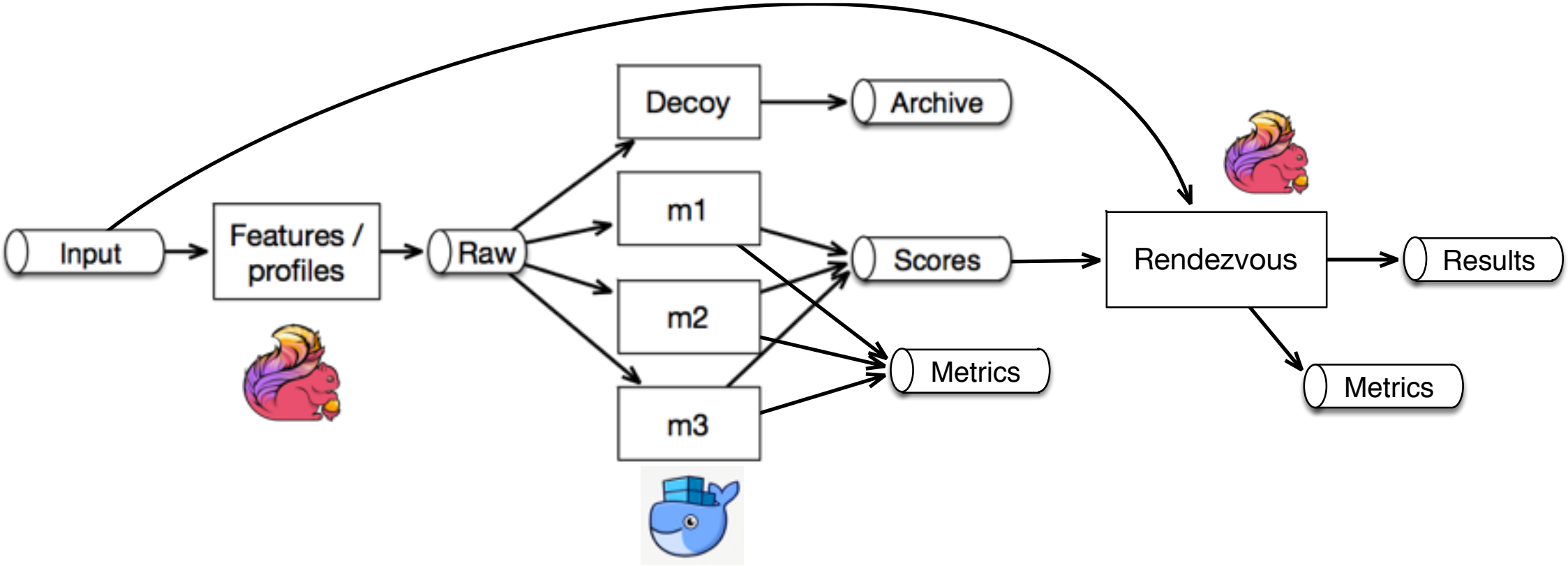
How to Do Better – Containers and Rendezvous

- Select desired model result
  - Thompson sampling, dithering
  - Defaults after extraordinary delays
- Rendezvous with original input
  - Or carry origin meta-data
- Record metrics
  - Latency
  - Score distributions
  - Selected model







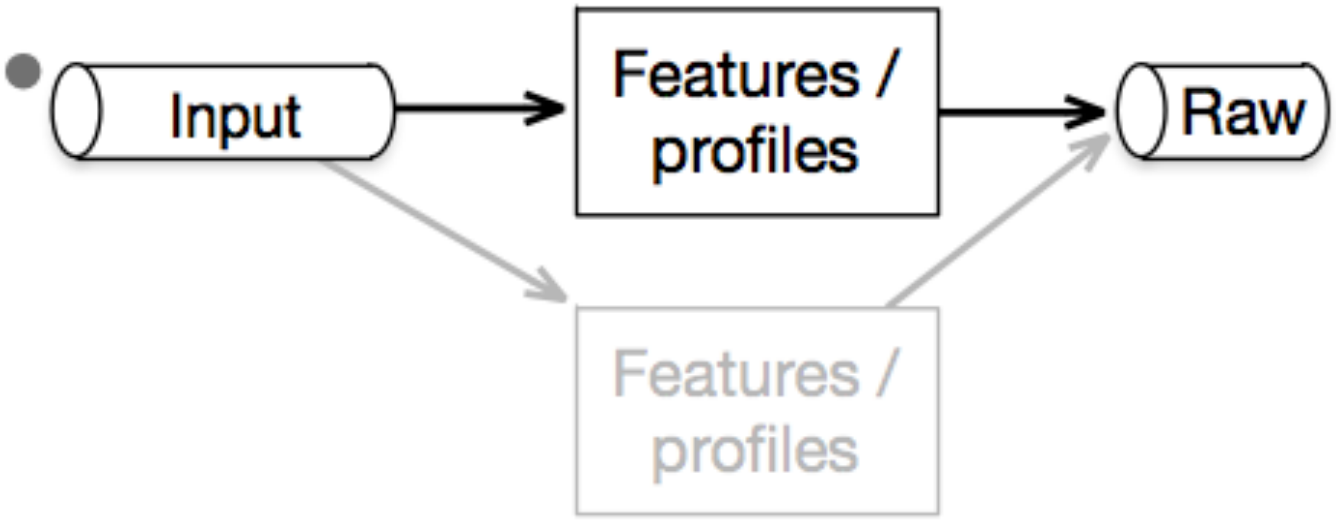


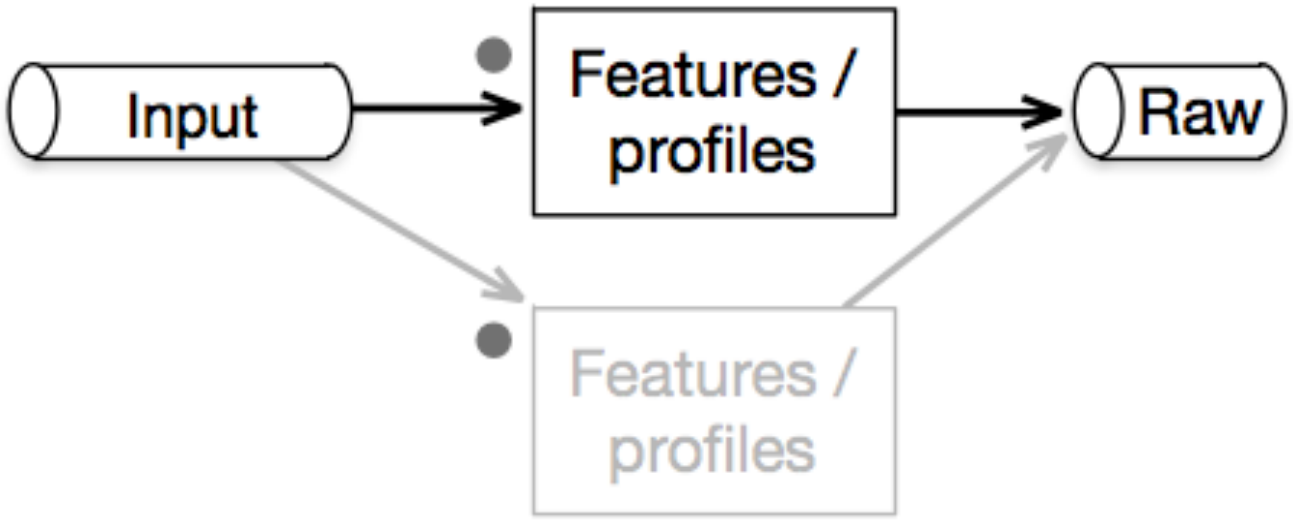
How to Do Better – Model Deployment as a Data Op

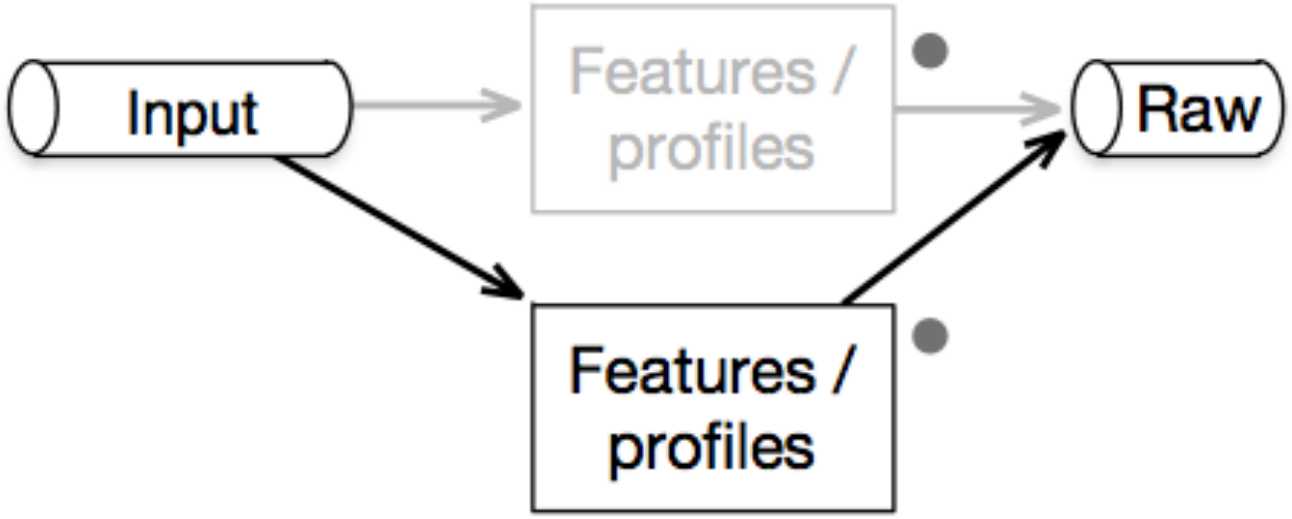
- Deploying a new model means spin some new containers
- Results will flow into the scoring stream
  - And will be ignored (initially)
- Tell the rendezvous service to use new model results
  - Start slowly
  - Check latencies, delta versus champion and canary
- Rendezvous service needs fallback rules
  - Use m3, after x ms use m2 if available, after y ms more, use m1
  - Must ***always*** give some answer within the SLA
  - Fancy statistics possible

Who Deploys the Deployer?

- Flink savepoints can be used to deploy new feature extractor, rendezvous service
- Underlying Chandry-Lamport algorithm can also be coded explicitly (not recommended for most folks)
- Hot swap token propagates through system to indicate when to switch







Takeaways

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- Prioritize – put serious effort into infrastructure
- Persist – use streams to keep data around
- Measure – everything, and record it
- Meta-analyze – understand and see what is happening
- Containerize – make deployment repeatable, easy

- Oh… don't forget to do some machine learning, too

Resources

- General principles of ML engineering with a Googlish accent:
  http://bit.ly/ml-best-practices-1

- More good practices:
  http://bit.ly/ml-best-practices-2

- Best short feature on feature engineering I know about:
  http://bit.ly/feature-engineering-1

Who I am

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Q&A

Engage with us!

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