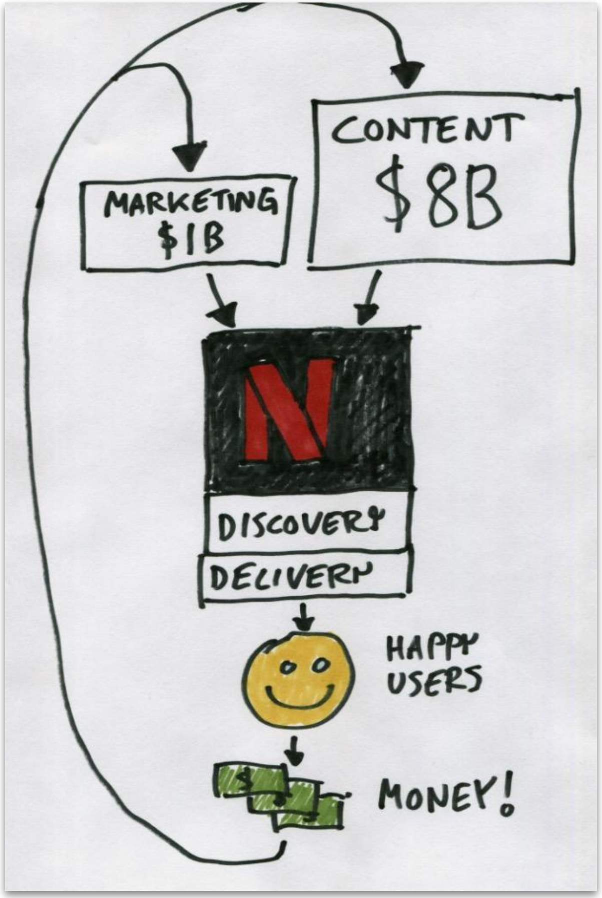
Machine Learning Infrastructure at Netflix

July 12th 2019
Savin Goyal

ML INFRA

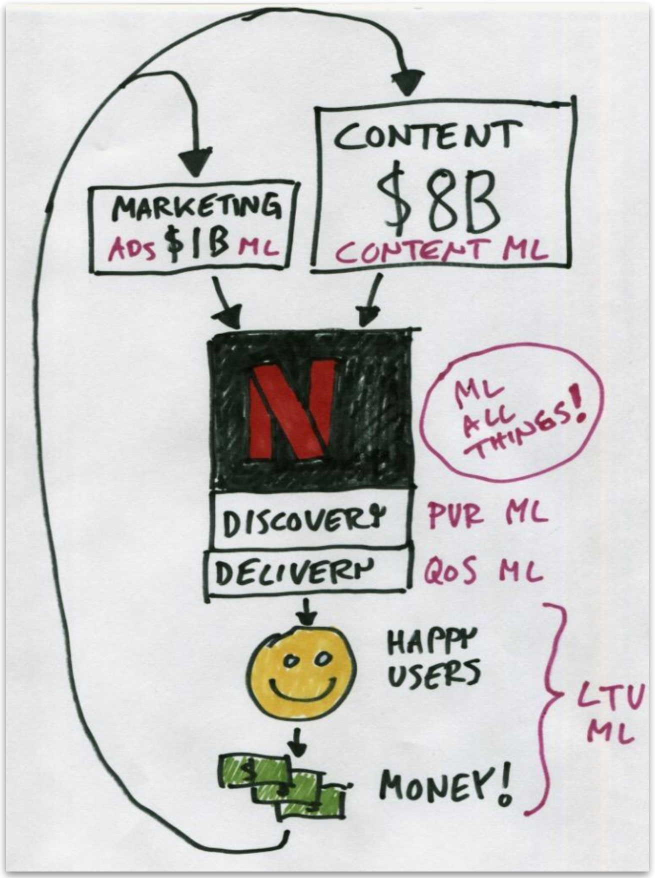
This is a high-level view of what Netflix does.



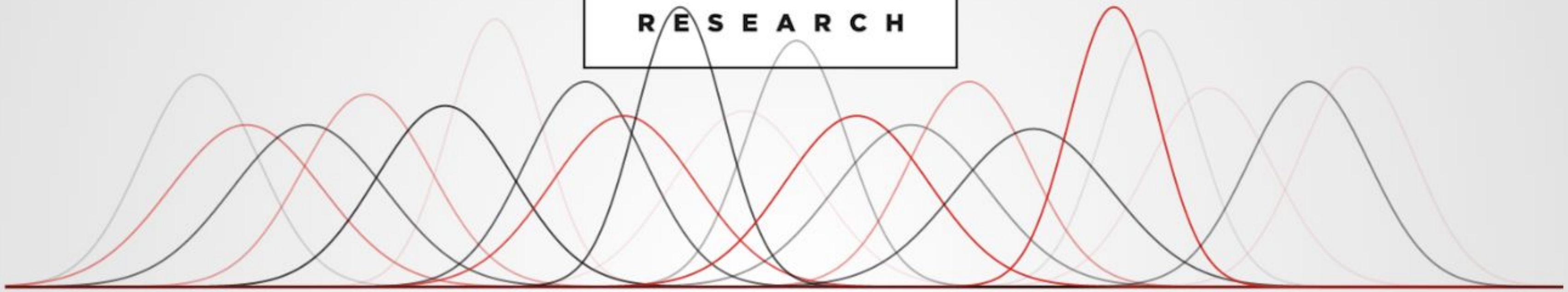
It is probably necessary to **get smarter** about everything:

- Content acquisition
- Marketing
- Discovery
- Delivery
- and more.

ML gets applied everywhere!



NETFLIX RESEARCH



Content Valuation

Optimize Production Schedules

Screenplay Analysis Using NLP

Predict Quality of Network

Intelligent Infrastructure

Machine Translation

Fraud Detection

Content Tagging

Predict Churn

Classify Support Tickets

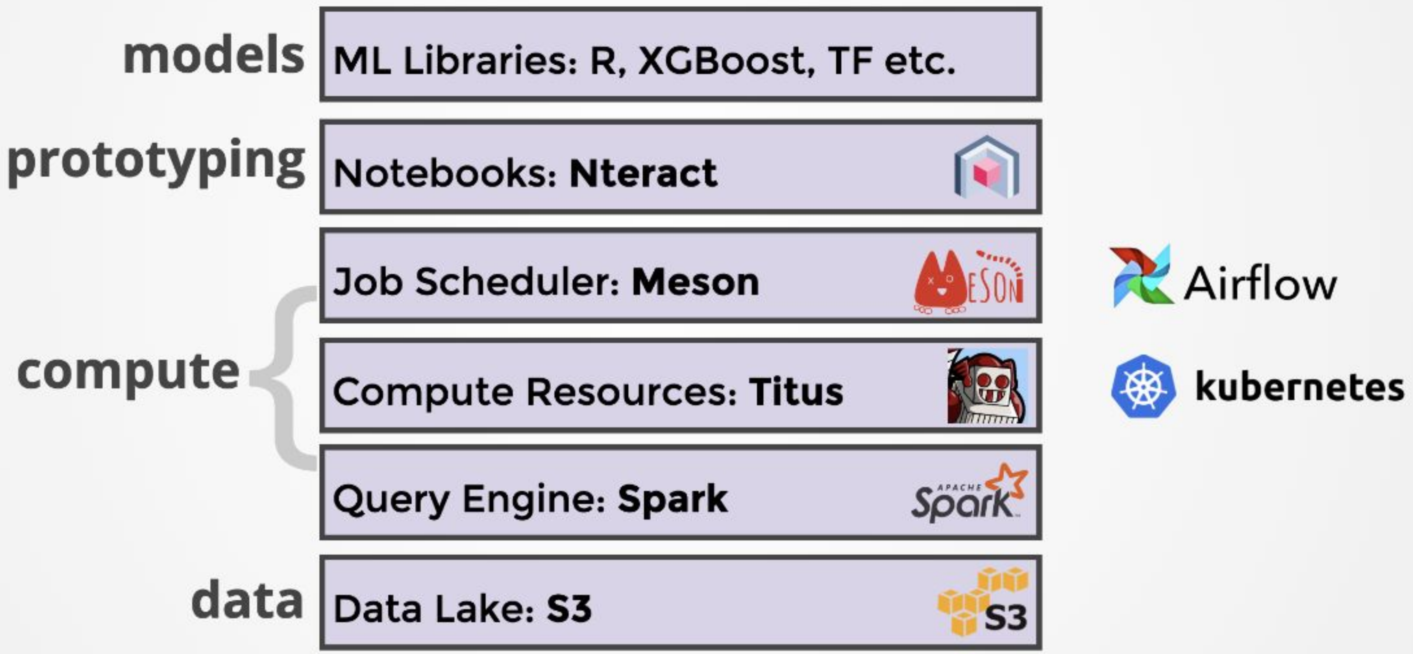
Title Portfolio Optimization

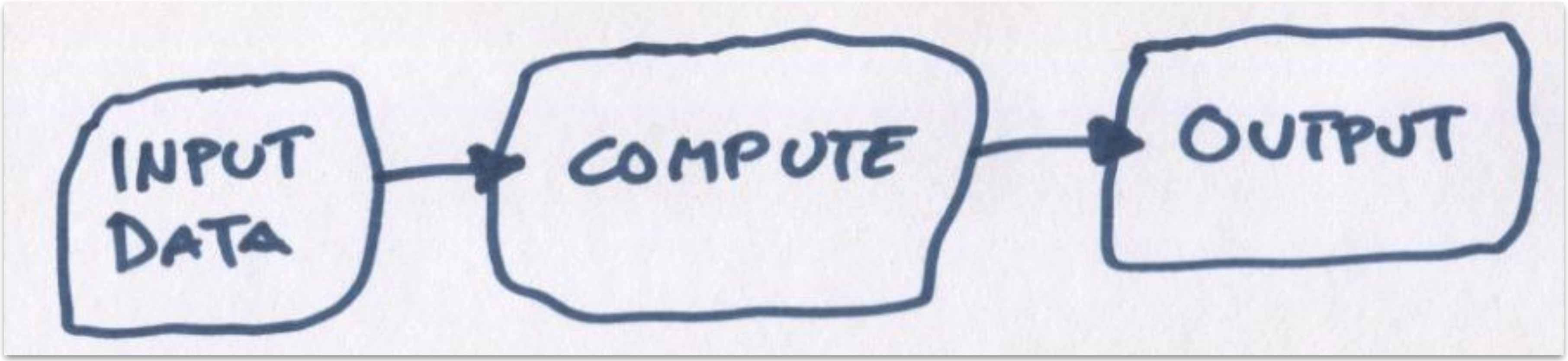
Incremental Impact of Marketing

Estimate Word-of-Mouth Effects

Cluster Tweets

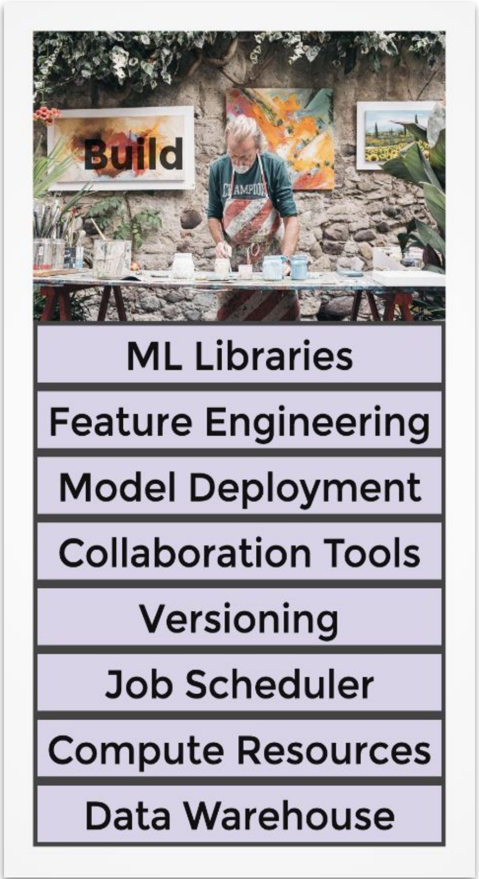
Optimal CDN Caching

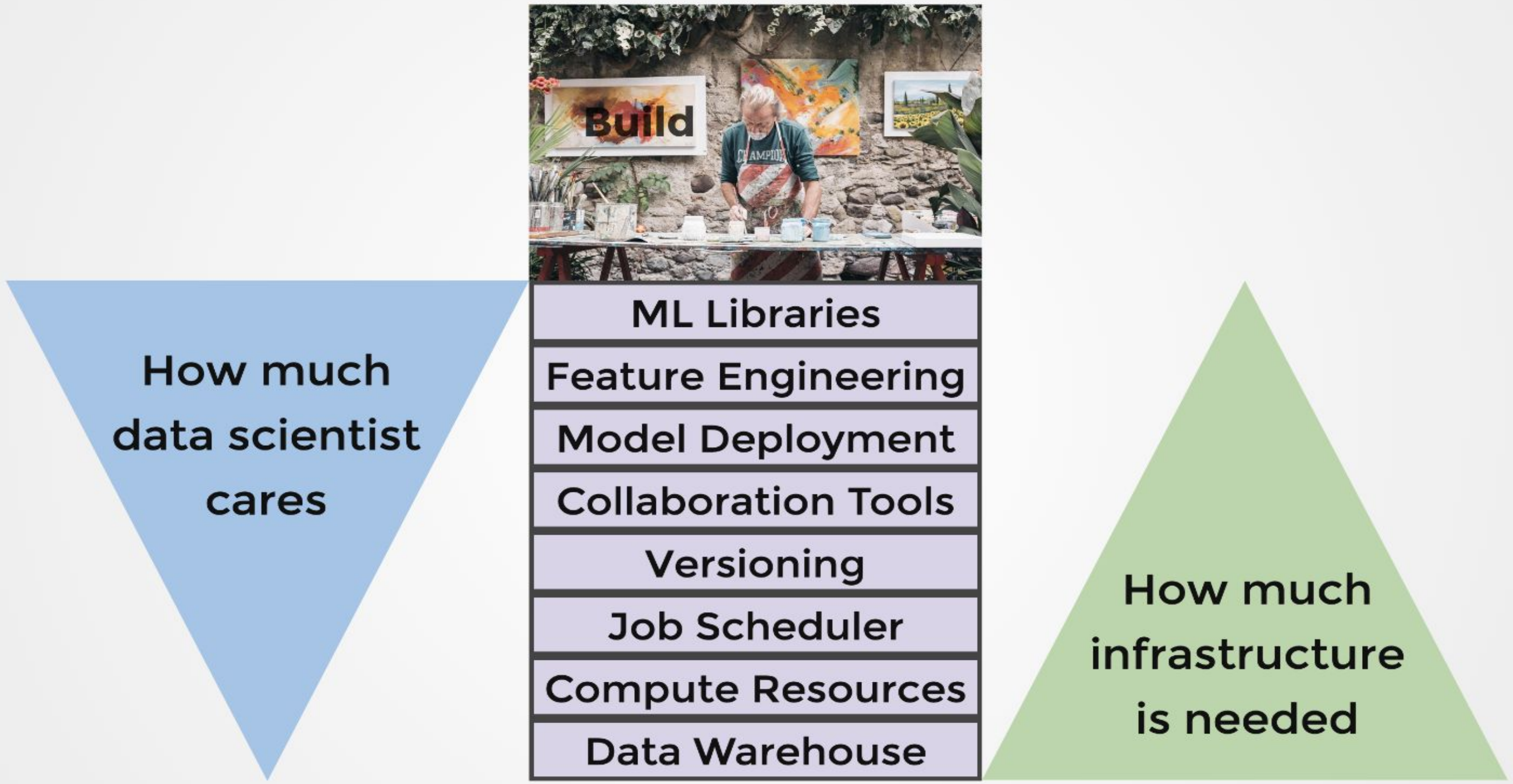

models
ML Libraries: R, XGBoost, TF etc.
prototyping
Notebooks: **Nteract**
compute
Job Scheduler: **Meson**
Compute Resources: **Titus**
Query Engine: **Spark**
data
Data Lake: **S3**
Airflow
kubernetes


INPUT DATA
COMPUTE
OUTPUT

Reality is not that straight-forward:

- How to run at scale?
- How to access data at scale?
- How to schedule the model to update daily?
- How to monitor models in production?
- How to debug failed production runs?
- How to iterate on new versions?
- How to collaborate with other users?
- …
- ...





How much data scientist cares

ML Libraries
Feature Engineering
Model Deployment
Collaboration Tools
Versioning
Job Scheduler
Compute Resources
Data Warehouse

How much infrastructure is needed

METAFLOW

Translate your domain knowledge to models with low cognitive overhead using tools you know.

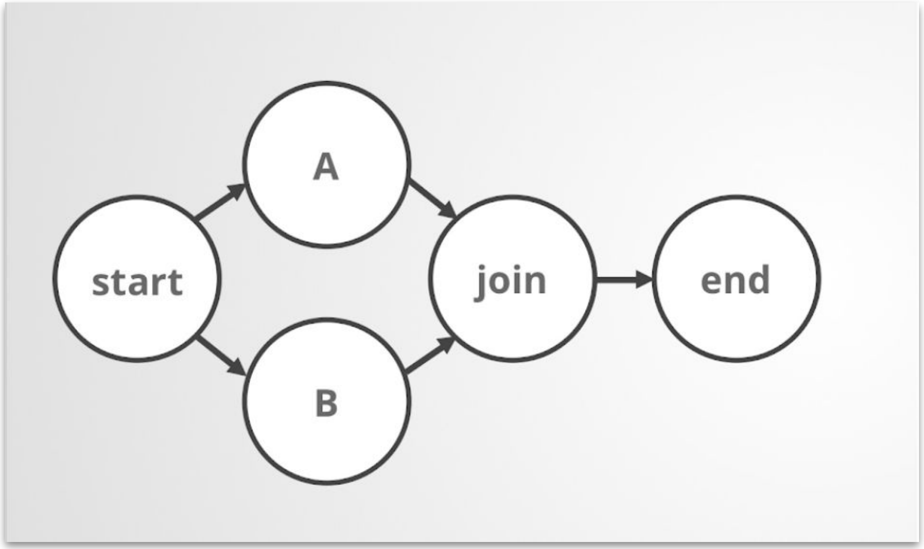
Easy path from exploration to business value.

Collaboration.

Structure your code as a DAG.

It is a natural way to express ML pipelines.

Many technical benefits follow when you do this.



```r
metaflow("BranchFlowR") %>%
  step(
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    r_function = start,
    next_step = c("a", "b")
  ) %>%
  step(
    step = "a",
    r_function = a,
    next_step = "join"
  ) %>%
  step(
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    next_step = "join"
  ) %>%
  step(
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    next_step = "end",
    join = TRUE
  ) %>%
  step(
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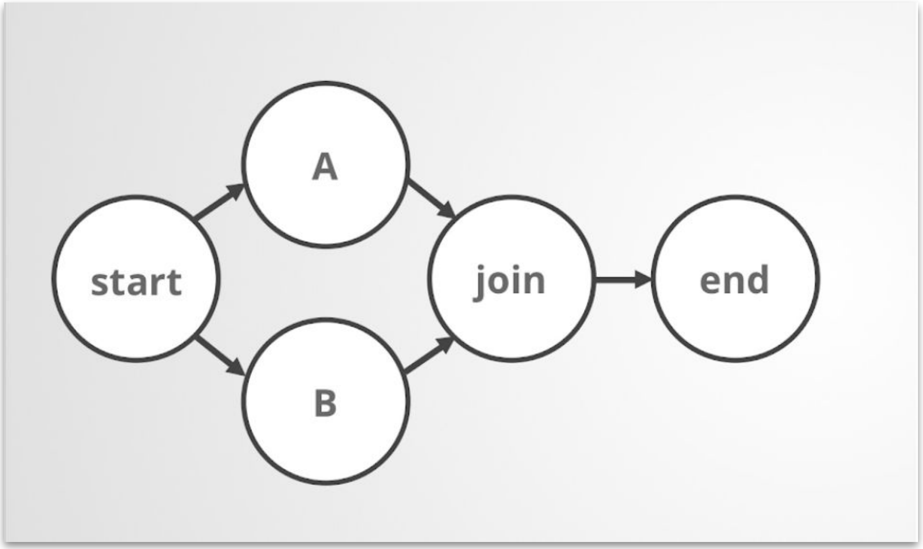
    r_function = end
  ) %>%
  run()
```



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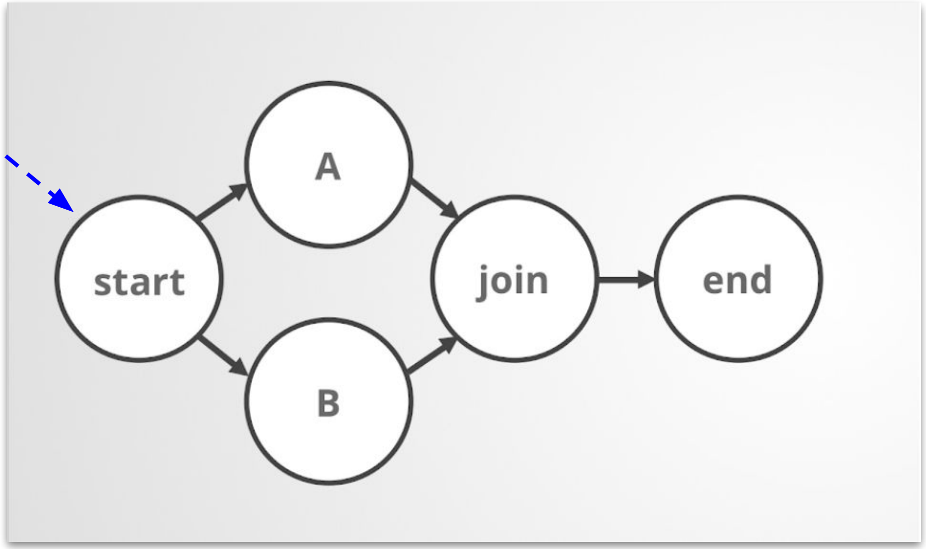

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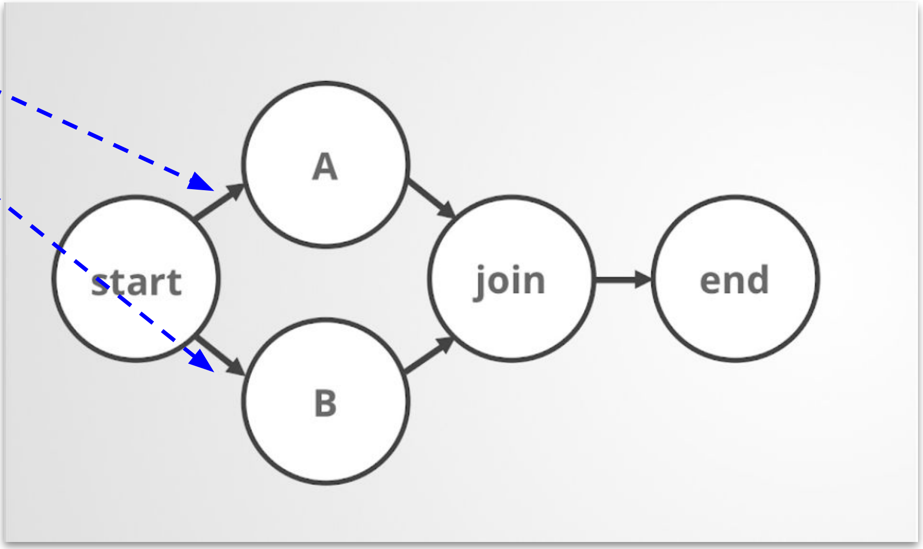

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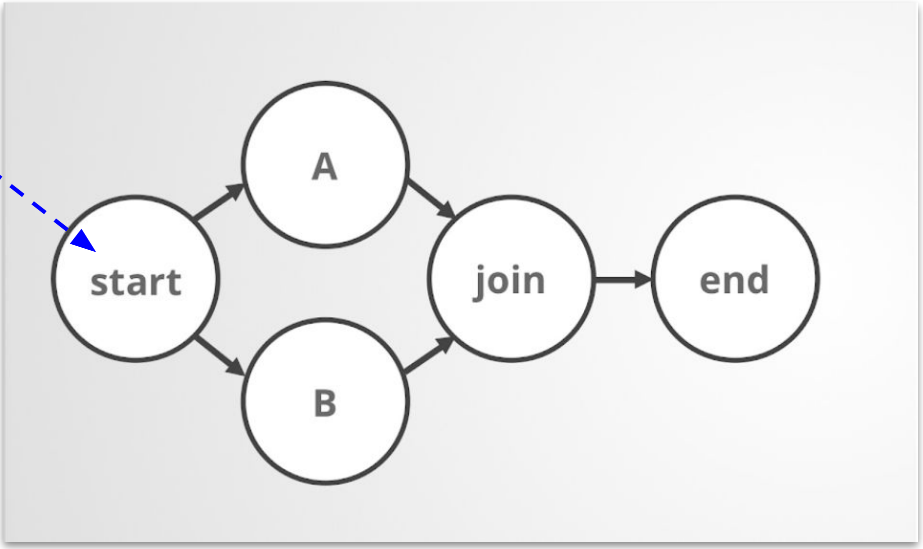
```

```r
start <- function(self) {
  self$my_var <- "hello world"
}
```



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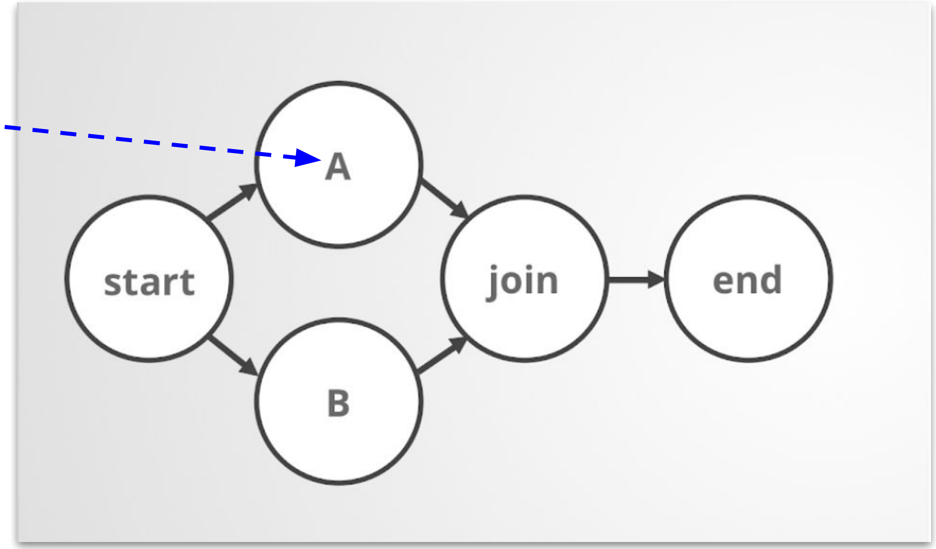

```r
a <- function(self) {
  message(
    "my_var is : ", self$my_var
  )
}
```

```r
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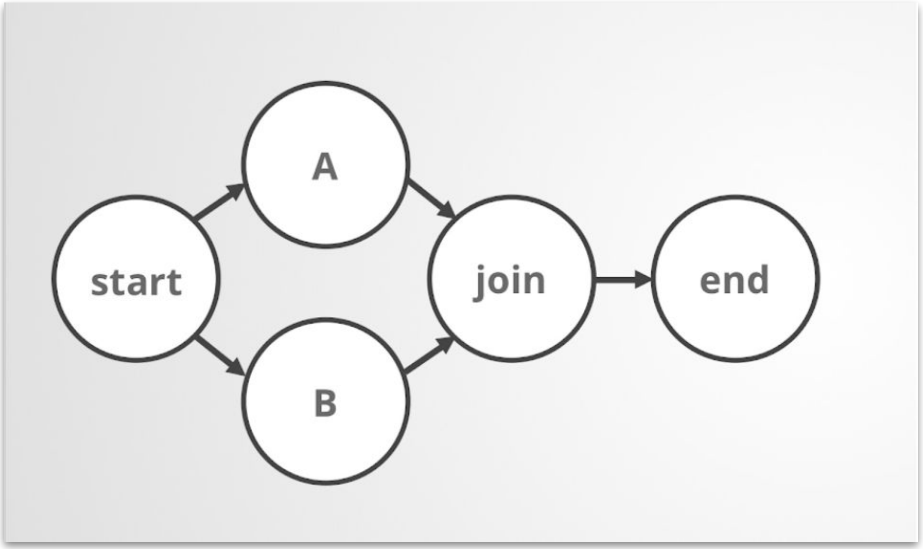
```

Execute as you would any R code



```
Rscript debug.R
```

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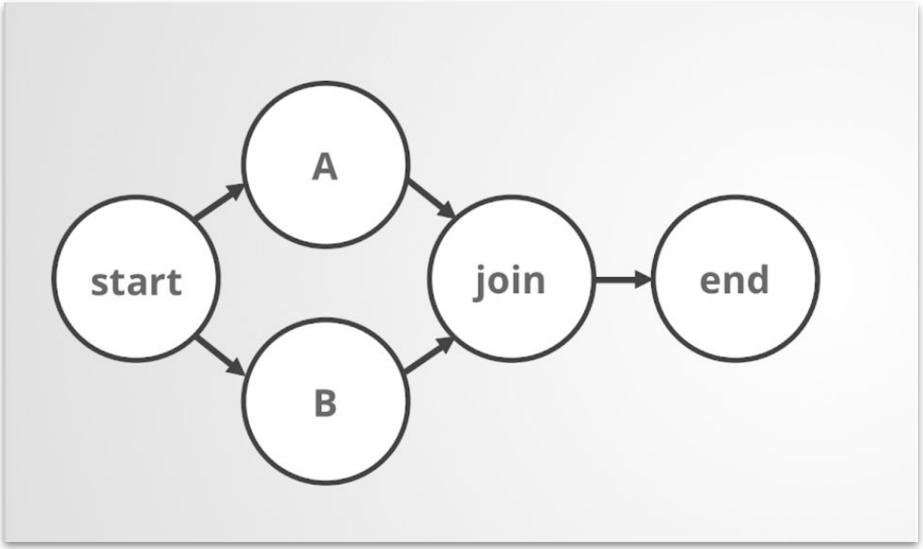
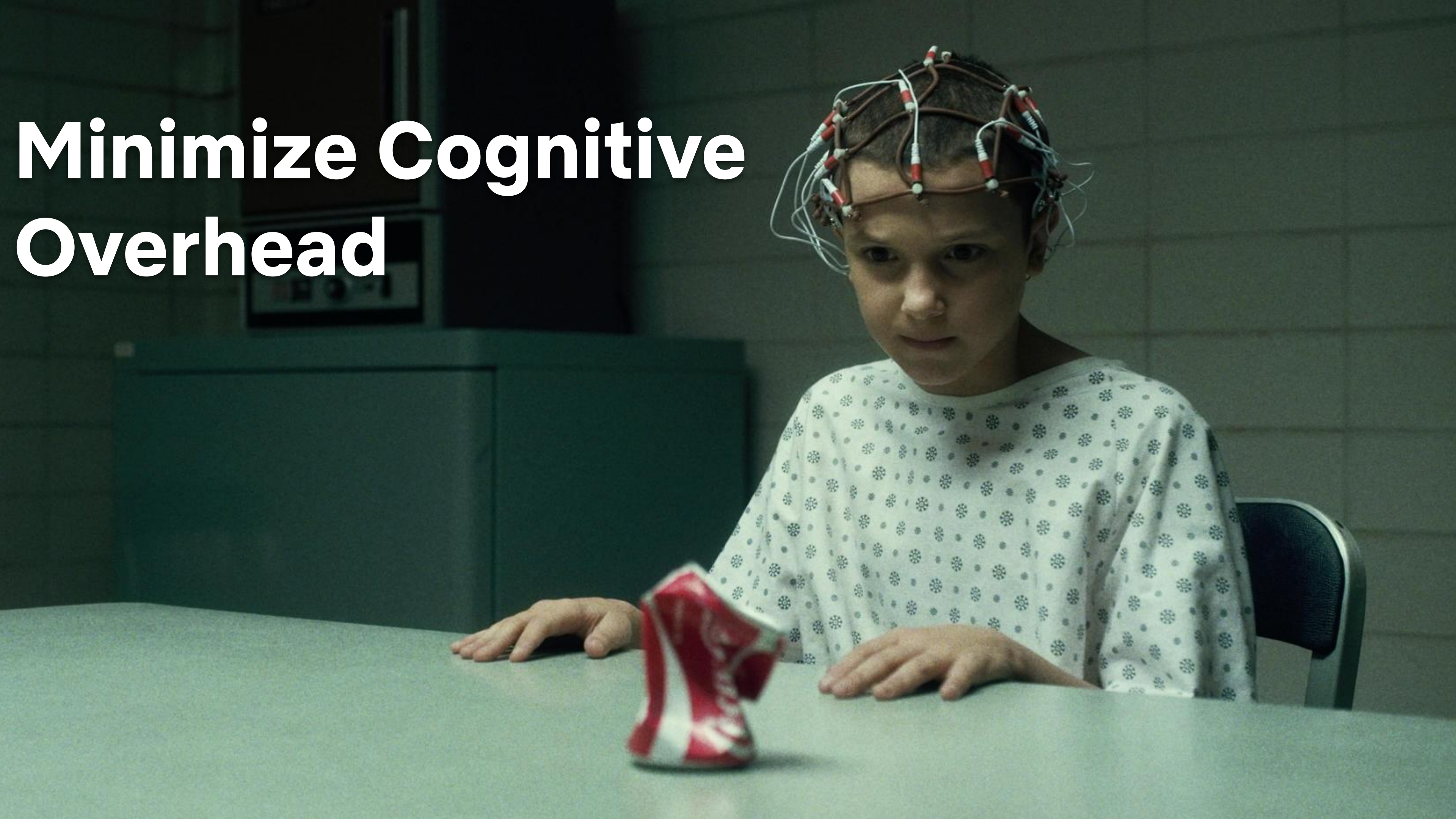
```

Checkpointing by default



```
Rscript debug.R resume
```

Minimize Cognitive Overhead



Keep using tools and libraries you are familiar with.

Dedicate your cognitive bandwidth on data science.

Metaflow stays out of your way.

No artificial limitations. Explore freely!

```r
fit_models <- function(self) {
  library(caret)
  param <- self$input
  train_control <- trainControl(
    method = "cv",
    number = 5
  )
  grid <- data.frame(
    interaction.depth = param$interaction.depth,
    shrinkage = param$shrinkage,
    n.trees = param$n.trees,
    n.minobsinnode = param$n.minobsinnode
  )
  x <- self$features
  y <- self$labels
  gbmfit <- train(
    x = x,
    y = y,
    method = "gbm",
    tuneGrid = grid,
    trControl = train_control,
    verbose = FALSE
  )
  self$model <- gbmfit$finalModel
  self$fit <- gbmfit$results
}
```

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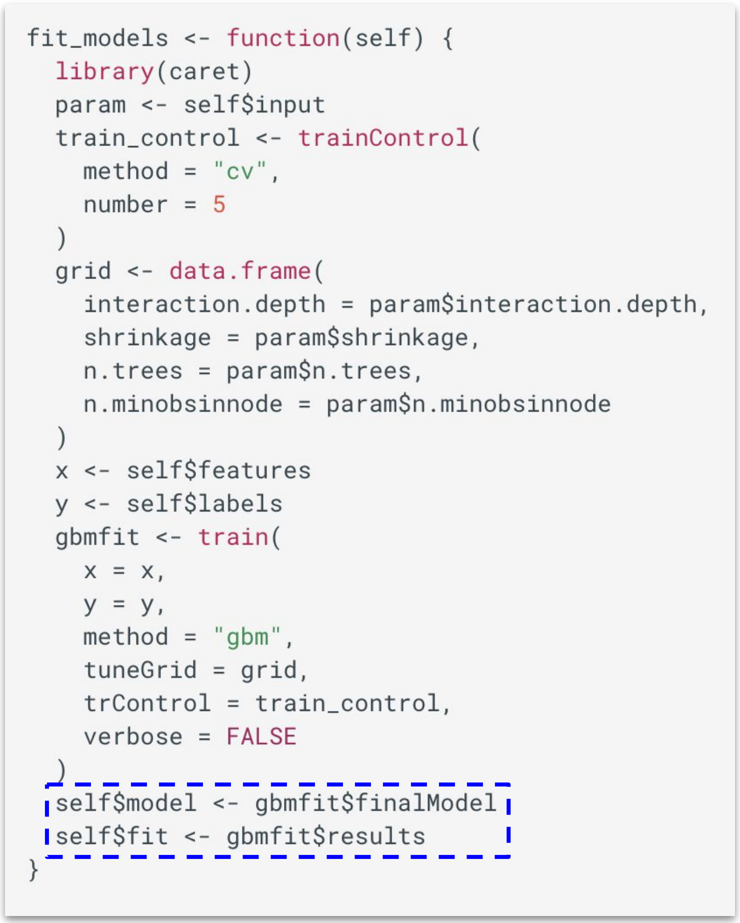

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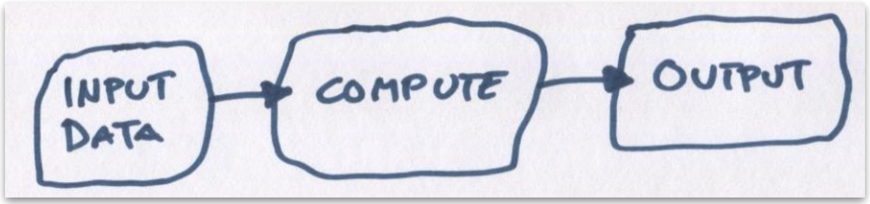
```

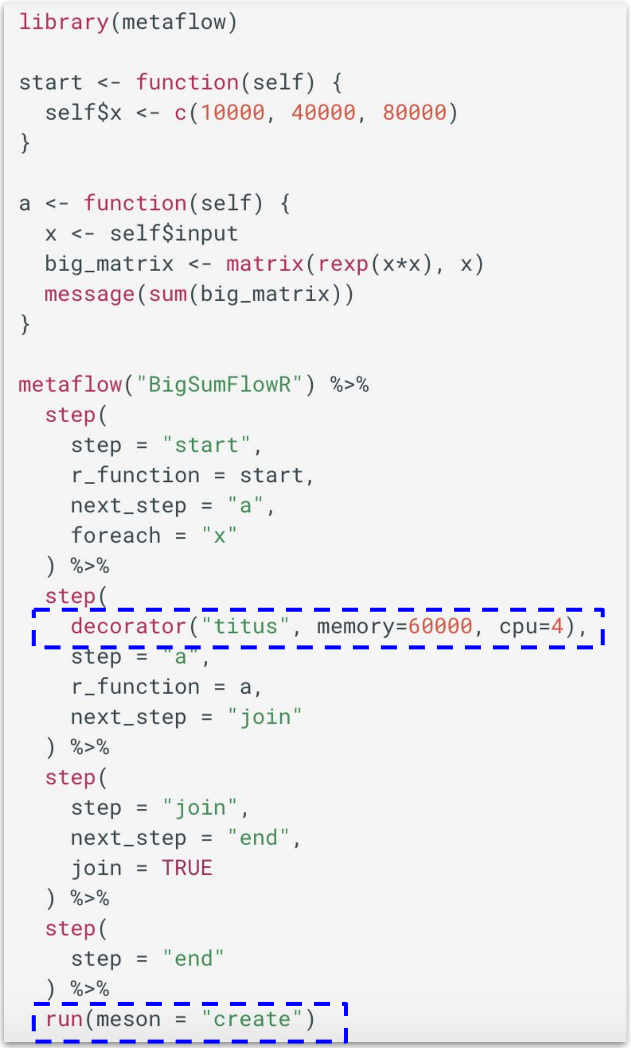
Focus on the following:

- Feature engineering.
- Training logic.
- Format of the output.



Metaflow takes the pain away from distractions like:

- Scalability.
- Scheduling.
- Operations.

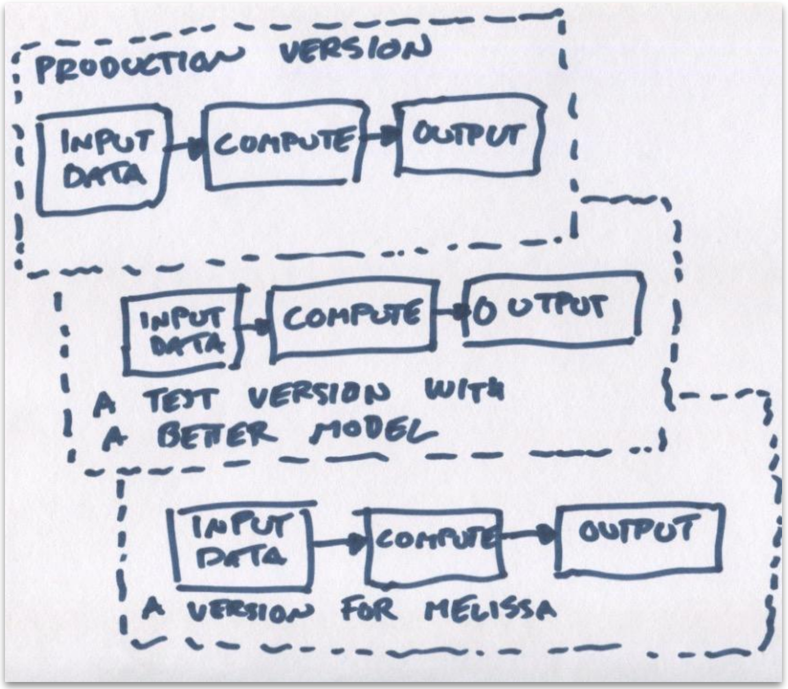


```r
library(metaflow)

start <- function(self) {
  self$x <- c(10000, 40000, 80000)
}

a <- function(self) {
  x <- self$input
  big_matrix <- matrix(rexp(x*x), x)
  message(sum(big_matrix))
}

metaflow("BigSumFlowR") %>%
  step(
    step = "start",
    r_function = start,
    next_step = "a",
    foreach = "x"
  ) %>%
  step(
    decorator("titus", memory=60000, cpu=4),
    step = "a",
    r_function = a,
    next_step = "join"
  ) %>%
  step(
    step = "join",
    next_step = "end",
    join = TRUE
  ) %>%
  step(
    step = "end"
  ) %>%
  run(meson = "create")
```

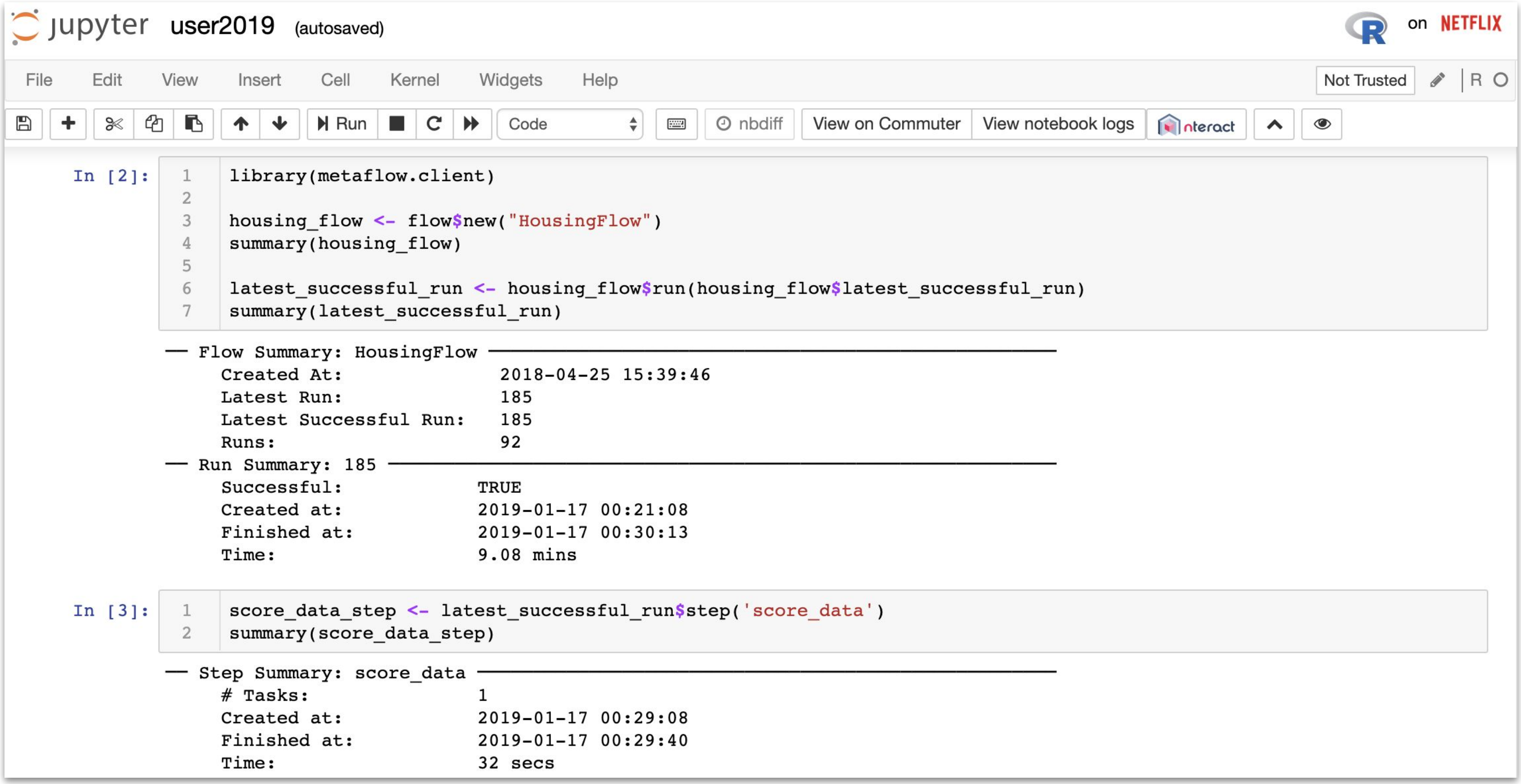
First Class Collaboration

I want to collaborate with other people but I don't want to think about it all the time!

- Everything is versioned.
- Everything can be tagged with human-readable annotations.
- All data artifacts are stored.
- Easy access to all code, data, & results.



Monitor models and examine results



In [2]:
```
library(metaflow.client)

housing_flow <- flow$new("HousingFlow")
summary(housing_flow)

latest_successful_run <- housing_flow$run(housing_flow$latest_successful_run)
summary(latest_successful_run)
```

```
── Flow Summary: HousingFlow ──────────────────────────────────────────────────
    Created At:                 2018-04-25 15:39:46
    Latest Run:                 185
    Latest Successful Run:      185
    Runs:                       92
── Run Summary: 185 ───────────────────────────────────────────────────────────
    Successful:               TRUE
    Created at:               2019-01-17 00:21:08
    Finished at:              2019-01-17 00:30:13
    Time:                     9.08 mins
```

In [3]:
```
score_data_step <- latest_successful_run$step('score_data')
summary(score_data_step)
```

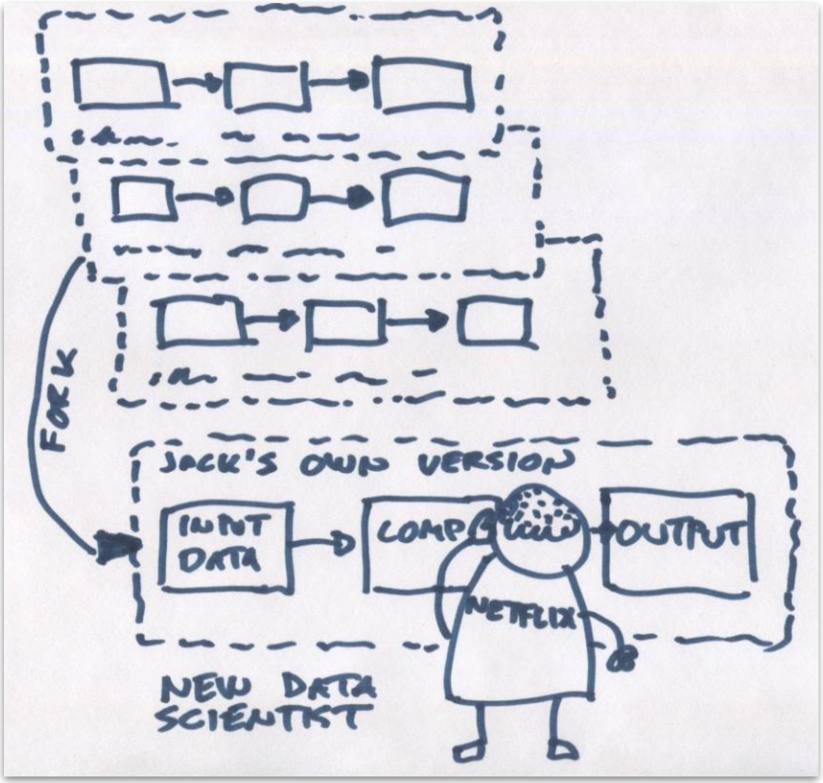
```
── Step Summary: score_data ───────────────────────────────────────────────────
    # Tasks:                  1
    Created at:               2019-01-17 00:29:08
    Finished at:              2019-01-17 00:29:40
    Time:                     32 secs
```

Reproducible Research

Metaflow solves the practical problem of being able to run the script again by:

- Storing **immutable snapshots** of code and data.
- Managing **external dependencies**.
- Maintaining a **detailed audit log** of all past runs, both during development and in production.

Gets us pretty close to the holy grail of reproducible research.



Many more features -

- Supports **Python** and **R**
- High-throughput **data access**
- Deploy models as **microservices**
- Flexible **parametrization** of workflows
- Isolated environments for **dependencies**
- **Slack** bot
- And more!

METAFLOW

Thank you!

savin@netflix.com

PS: We’re hiring!

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