Types, Types, Types!

Embracing a hierarchy of types to simplify machine learning

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Let’s make sure you are in the right talk

What I am going to talk about:

- What does machine learning mean at Salesforce
- Problems in machine learning for business to business (B2B) companies
- Automating machine learning and how our AutoML library (Optimus Prime) works
- The utility of having strongly typed features in AutoML
- What we have learned and what we are planning

Salesforce and Machine Learning

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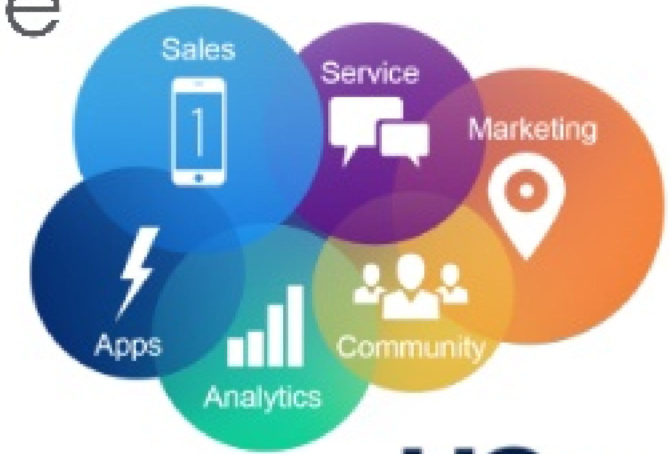

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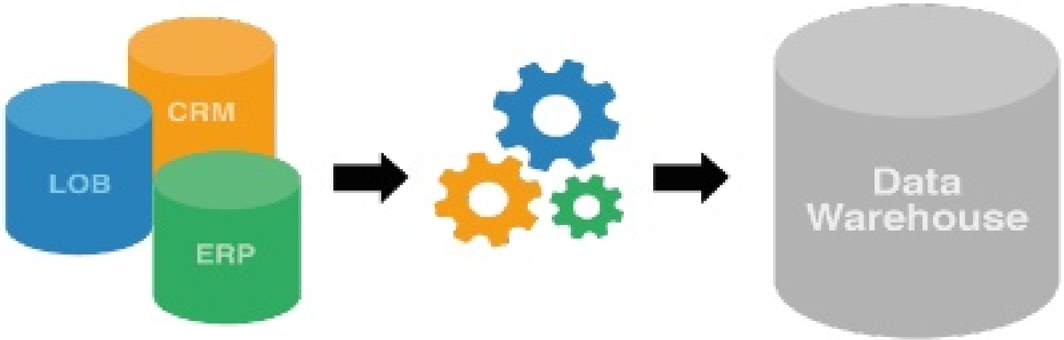
The Problem

For the majority of businesses, data science is out of reach

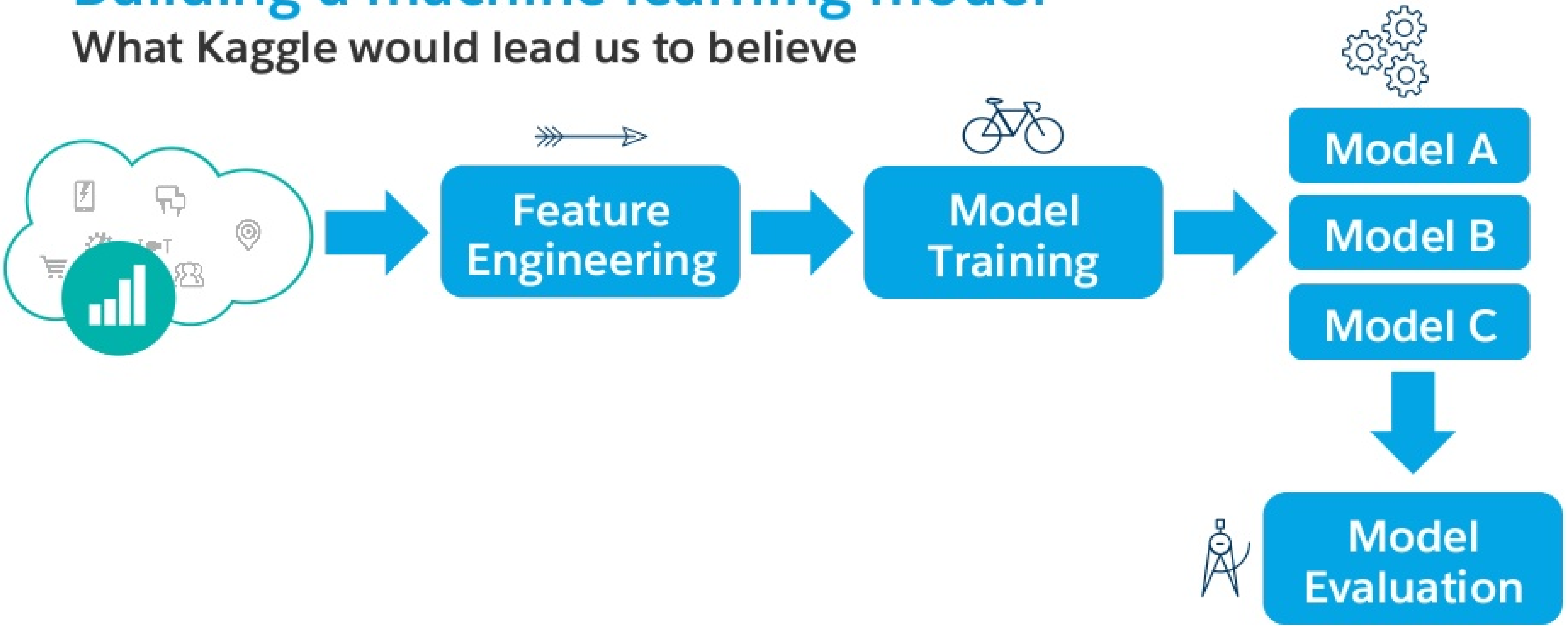


Machine learning workflows

And how much more complicated they get for B2B

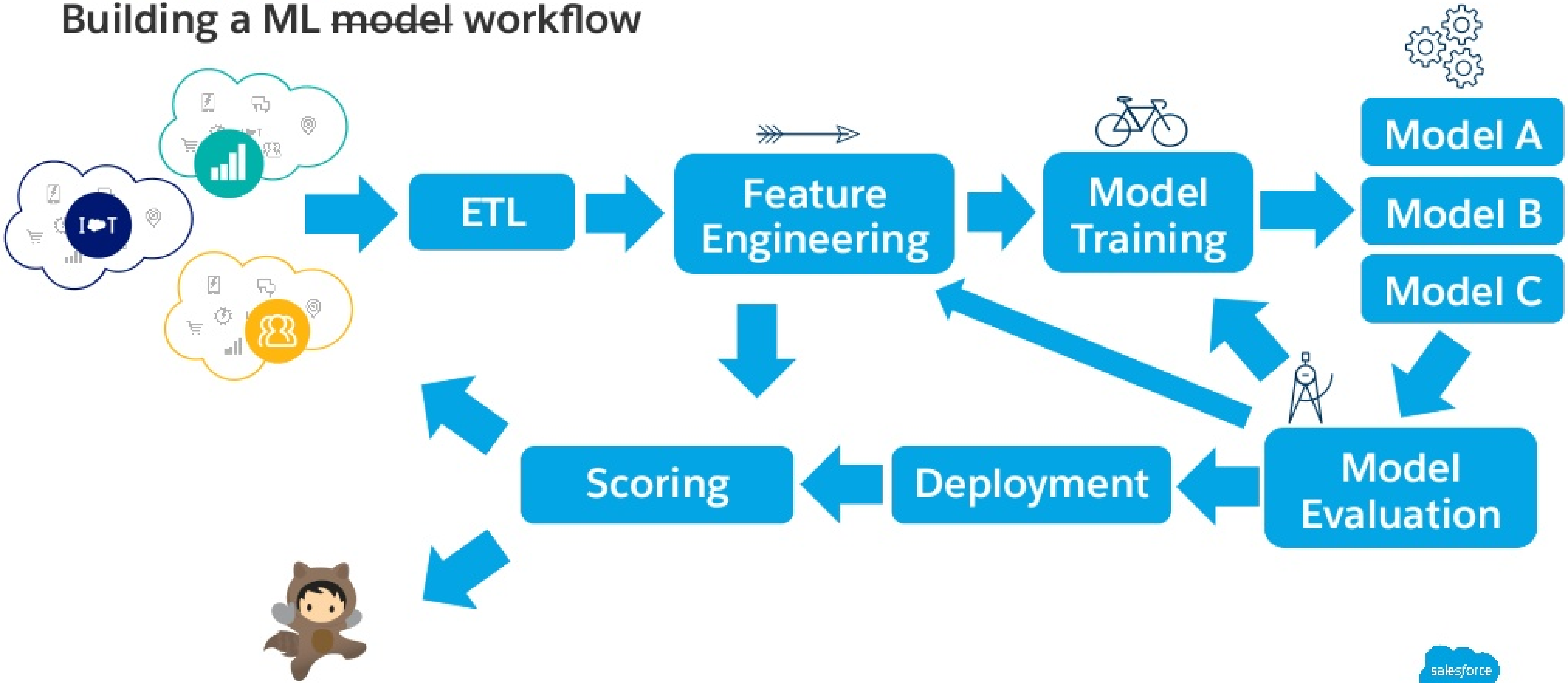
Building a machine learning model

What Kaggle would lead us to believe



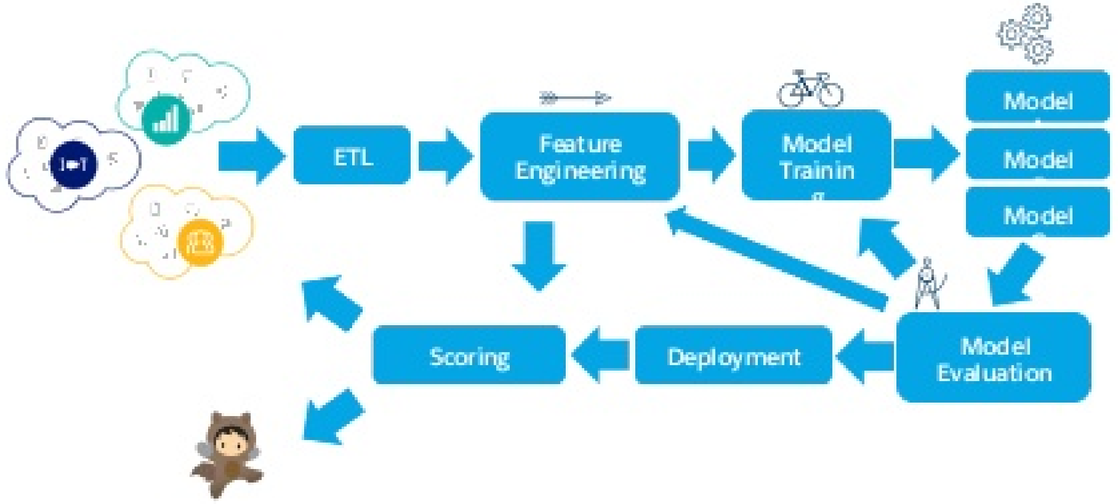
Real-life ML

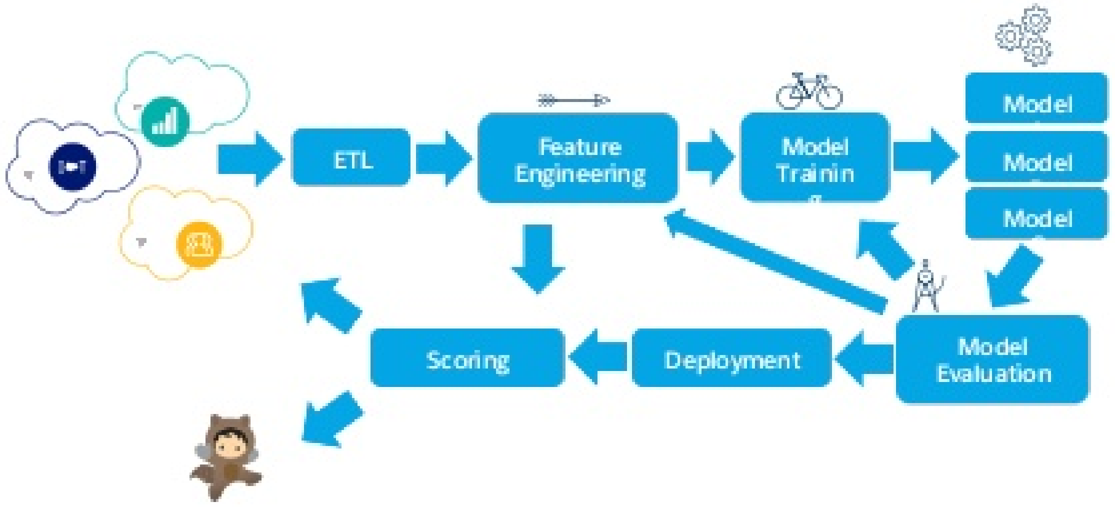
Building a ML ~~model~~ workflow

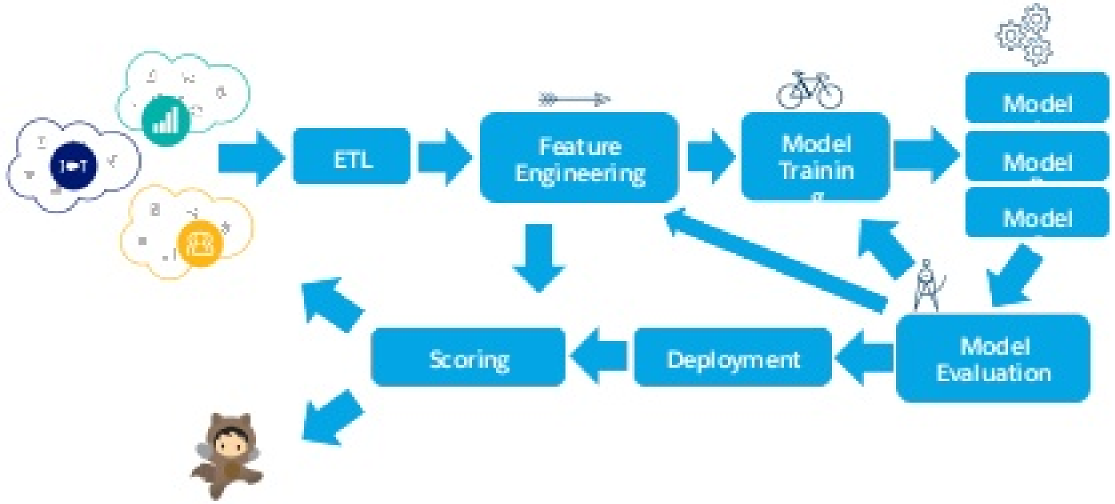


Building a machine learning model

Over and over again







We can’t build one global model

- Privacy concerns
  - Customers don’t want data cross-pollinated
- Business Use Cases
  - Industries are very different
  - Processes are different
- Platform customization
  - Ability to create custom fields and objects
- Scale, Automation,
  - Ability to create

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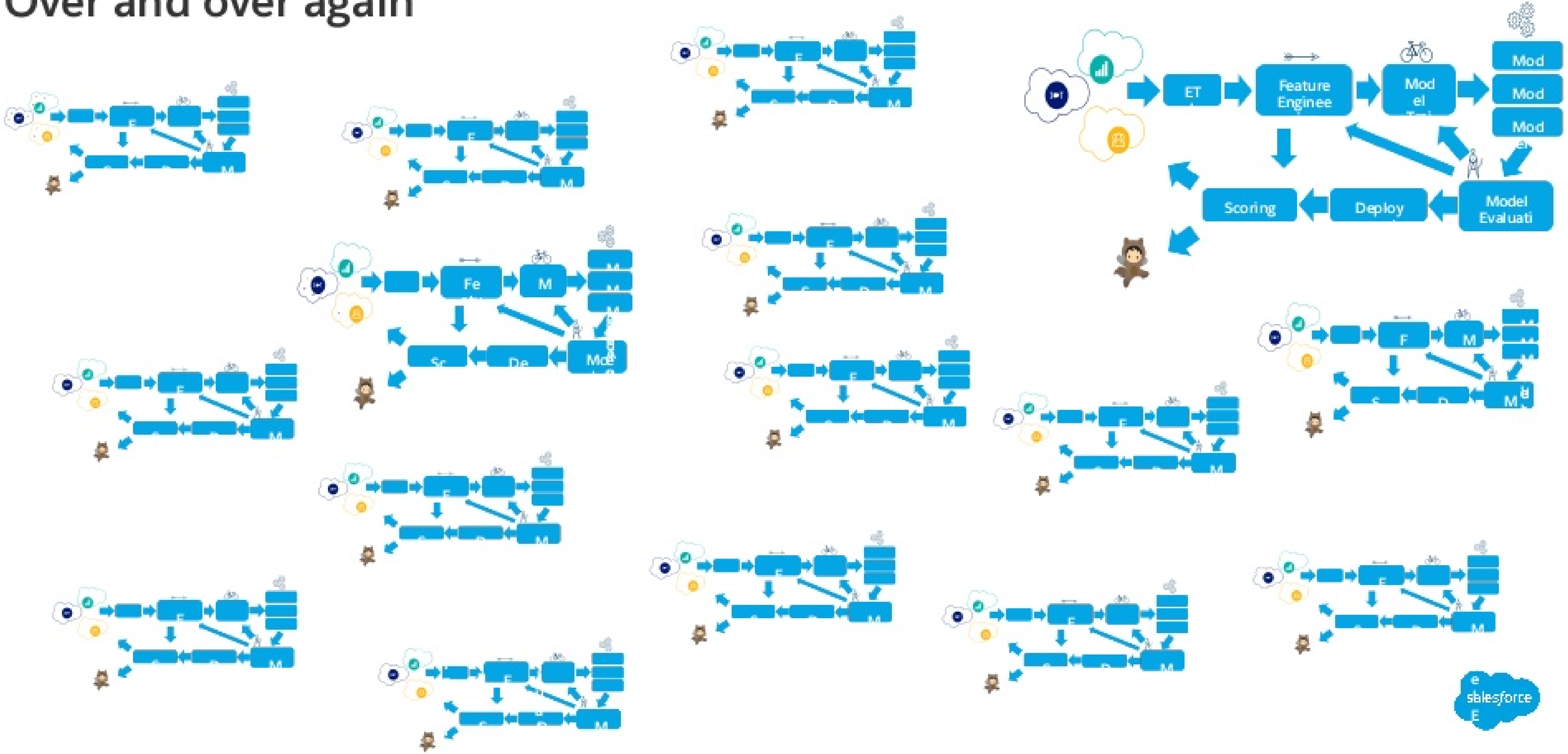
Building a machine learning model

Over and over again



Automating machine learning

Enter Einstein (and Optimus Prime)

Turning a black art into a paint by number kit.

- ML is not magic, just statistics – generalizing examples
- But there is a 'black art' to producing good models
  - Input data needs to be combined, filtered, cleaned etc.
  - Producing the best features for your model takes time
  - You can't just throw a ml algorithm at your raw data and expect good results

Keep it DRY (don't repeat yourself) and DRO (don't repeat others)

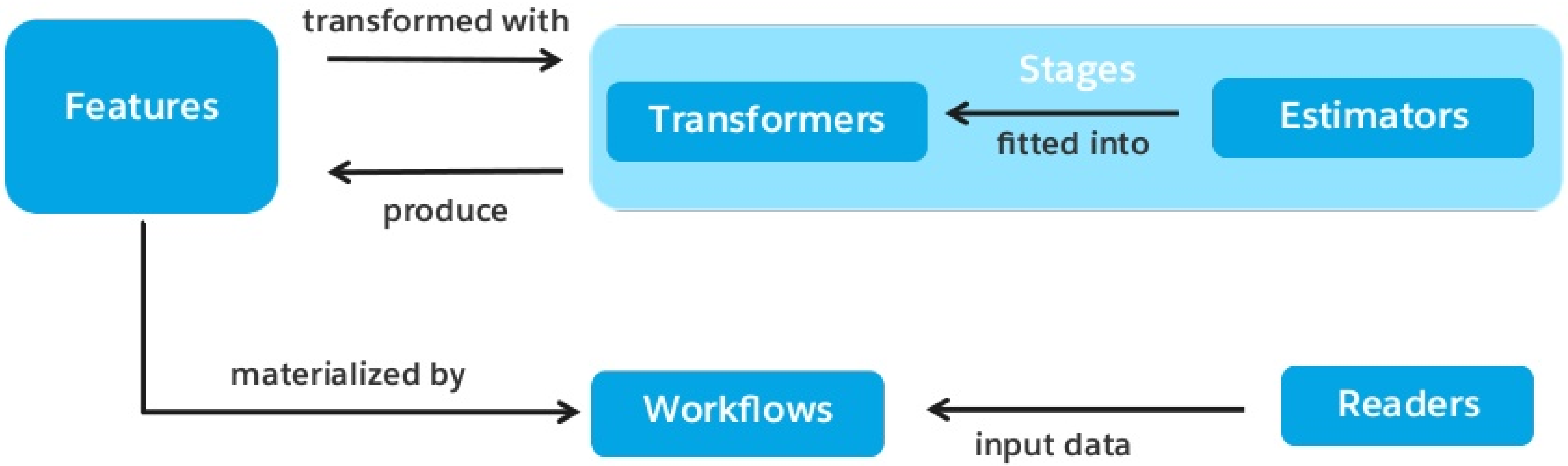
Optimus Prime - A library to develop reusable, modular and typed ML workflows

- The Spark ML pipeline (estimator, transformer) model is nice
- The lack of types in Spark is not
- Want to use more than Spark ML

- Declarative and intuitive syntax – for both workflow generation and developers
- Typed reusable operations
- Multitenant application support
- All built in scala

Simple interchangeable parts

In a declarative type safe syntax




```
val featureVector = Seq(pClass, name, gender, age, sibSp, parch, ticket, cabin, embarked).vectorize()
val (pred, raw, prob) =  featureVector.check(survived).classify(survived)
val workflow = new OpWorkflow().setResultFeatures(pred).setDataReader(titanicReader)
```

Automating typed feature engineering and modeling

(with Optimus Prime)

Features are given a type on creation

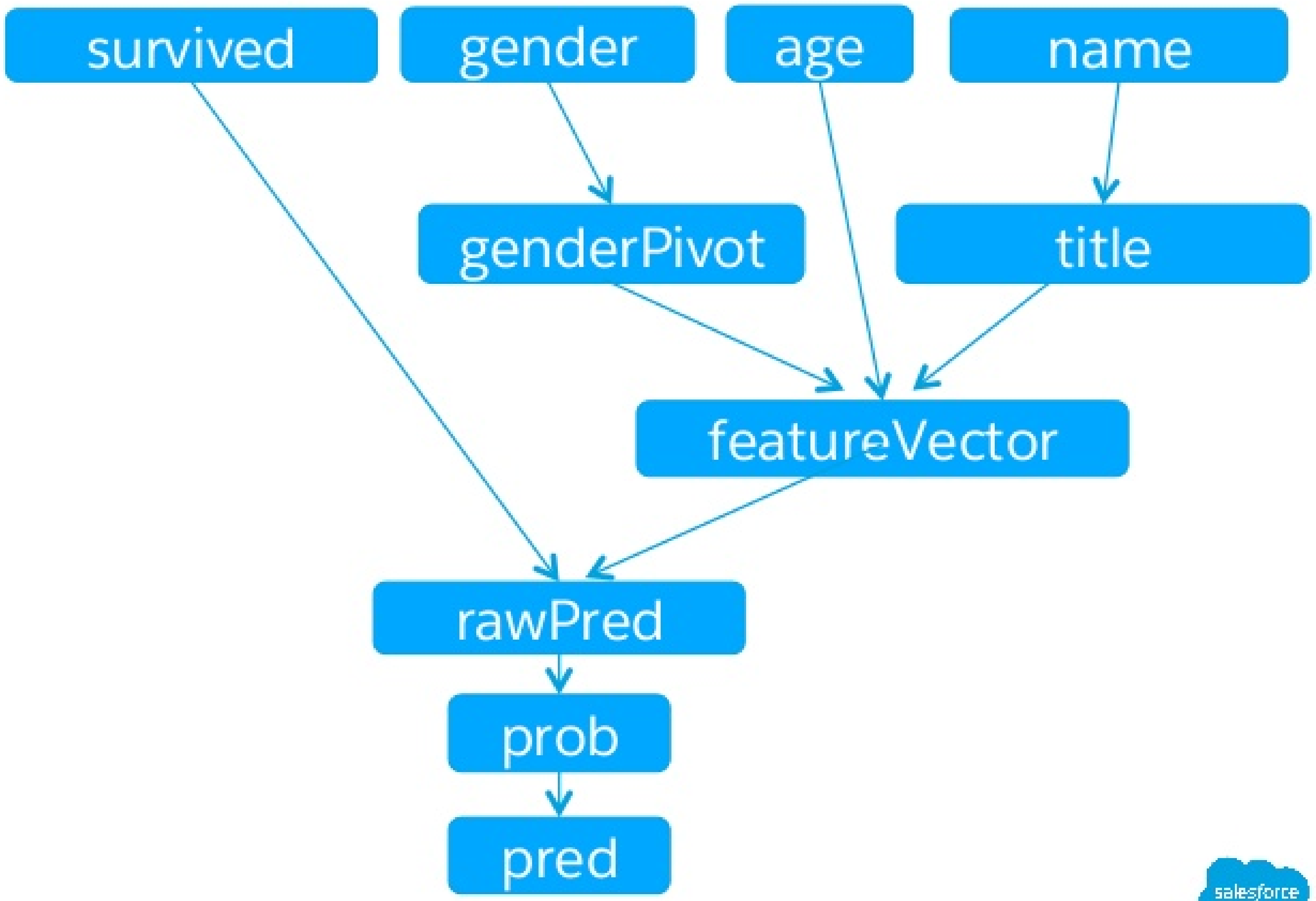
Death to runtime errors!


```
val gender = FeatureBuilder.Categorical[Titanic]
  .extract(d => Option(d.getGender).toSet[String]).asPredictor
```

- Features are strongly typed
- Each stage takes specific input type(s) and returns a specific output type(s)

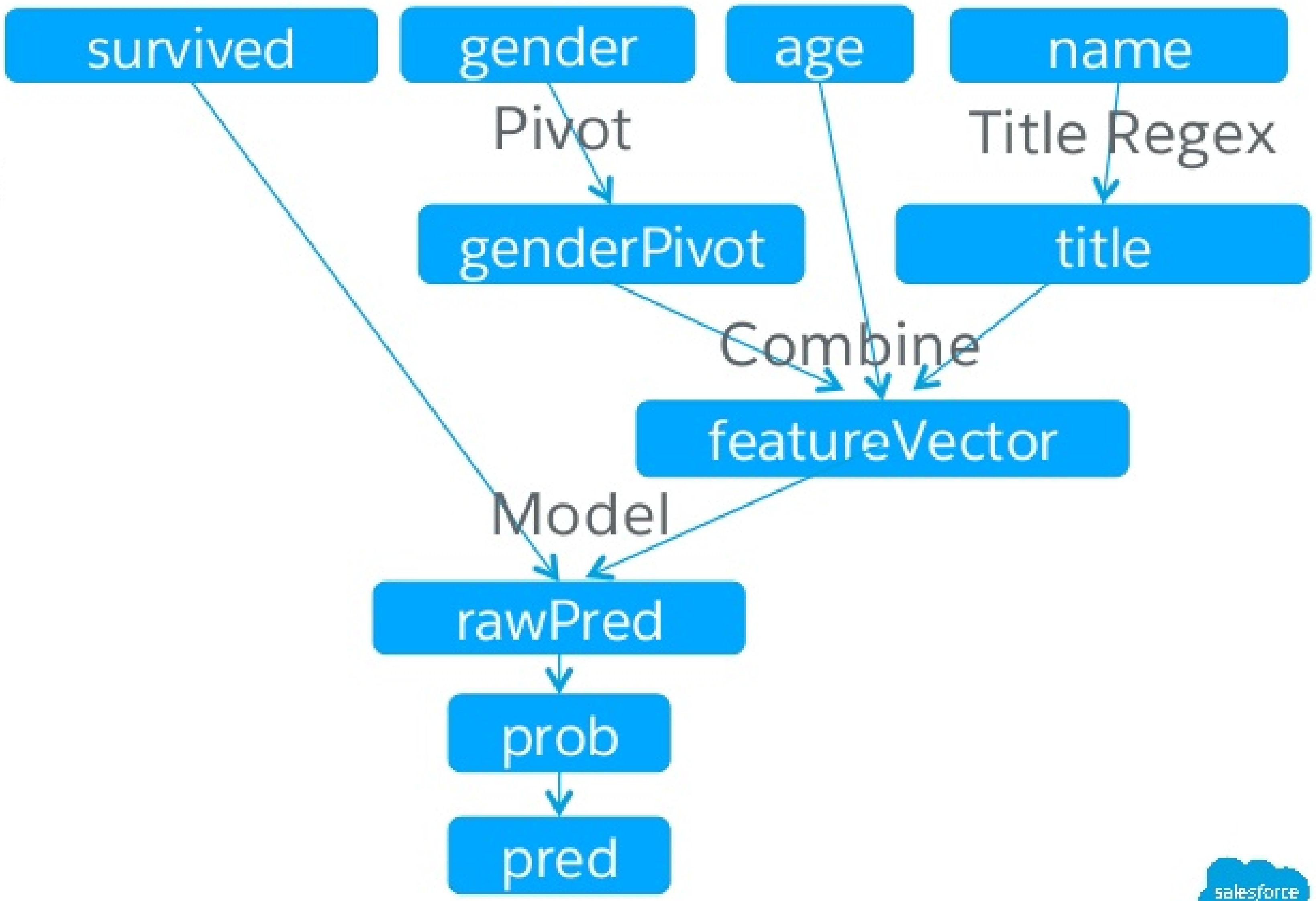
Creating a workflow DAG with features

- Features point to a column of data
- The type of the feature determines which stages can act on it

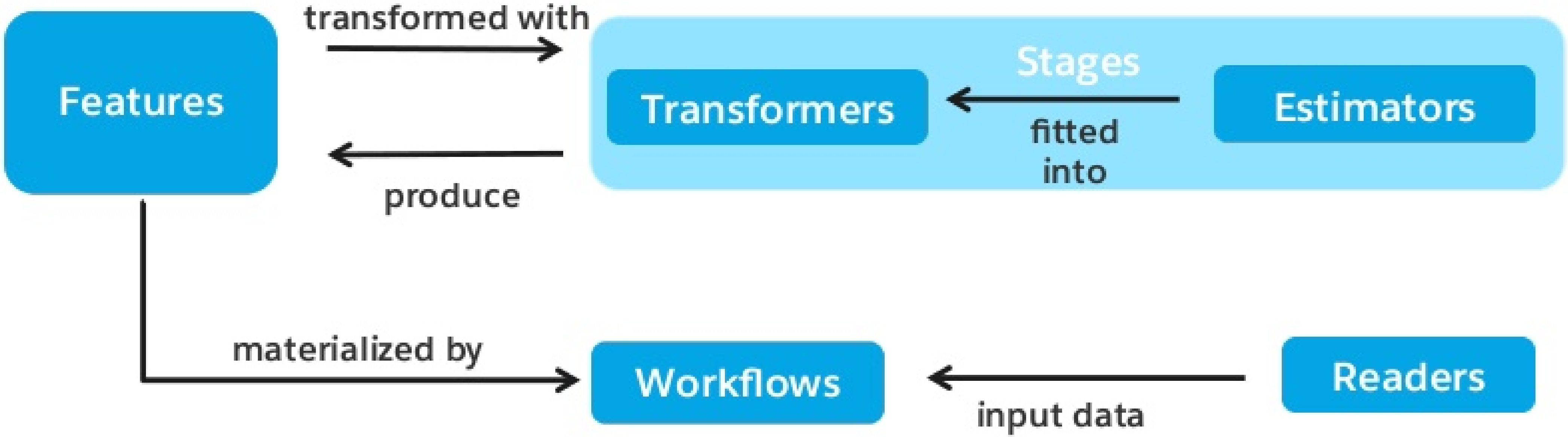


Creating a workflow DAG with features

- When a stage acts on a feature it produces a new feature (or features)
- Keep on manipulating features until you get your goal



Done manipulating your features? Make them.



- Once you make your final feature you have the full DAG
- Features are materialized by the workflow
- Initial data into the workflow provided by the reader

The power of types!

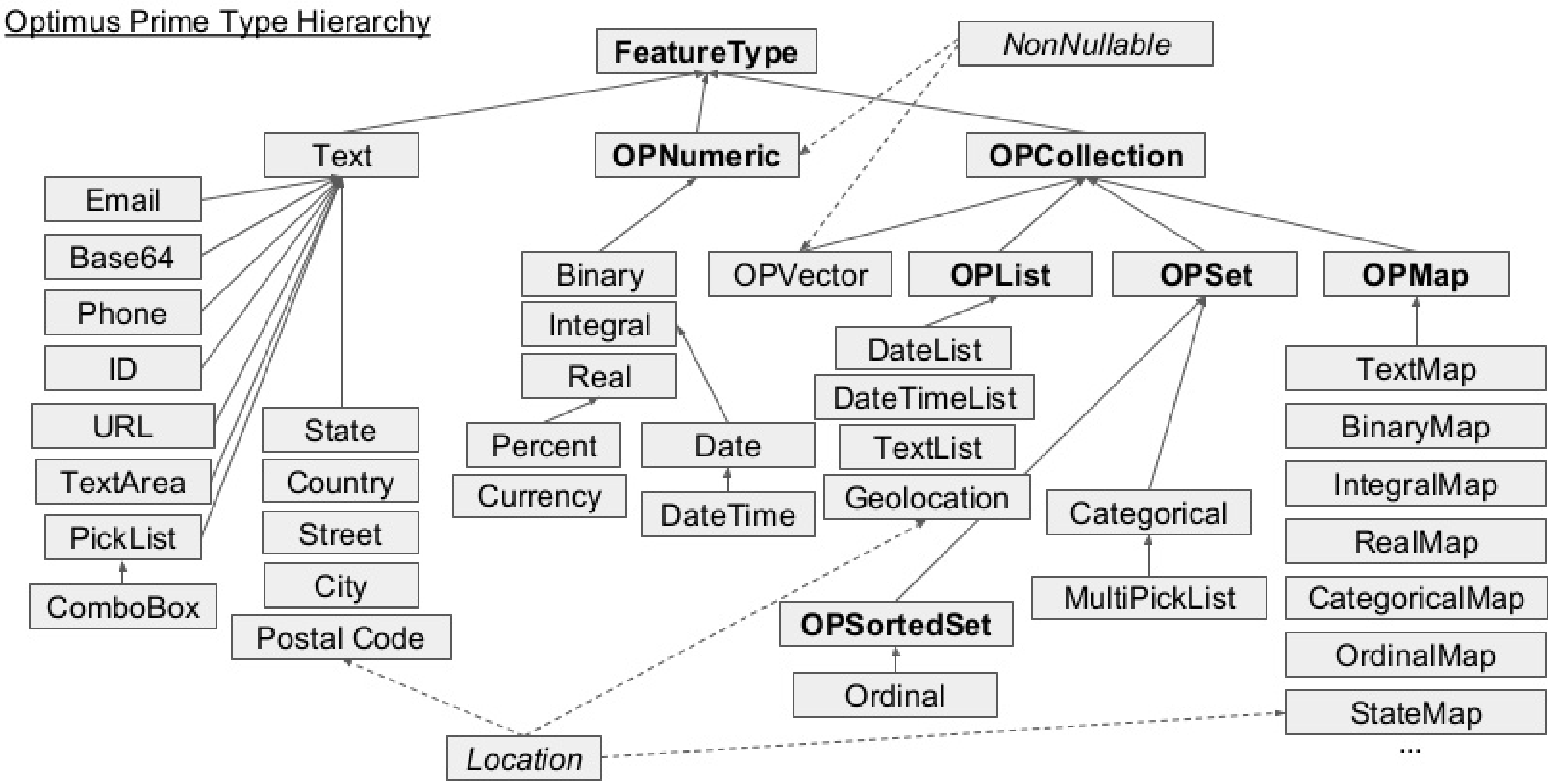
Using types to automate feature engineering

val *featureVector* = *Seq*(*pClass*, *name*, *gender*, *age*, *sibSp*, *parch*, *ticket*, *cabin*, *embarked*).vectorize()

- Each feature is mapped to an appropriate .vectorize() stage based on its type
  - *gender* (a Categorical) and *age* (a Real) are automatically assigned to different stages

- You also have an option to do the exact type safe manipulations you want
  - *age* can undergo special transformations if desired
  - val *ageBuckets* =*age*.bucketize(buckets(0, 10, 20, 40, 100))
  - val *featureVector* = *Seq*(*pClass*, *name*, *gender*, *ageBuckets*, *sibSp*, *parch*, *ticket*, *cabin*, *embarked*).vectorize()

Show me the types!



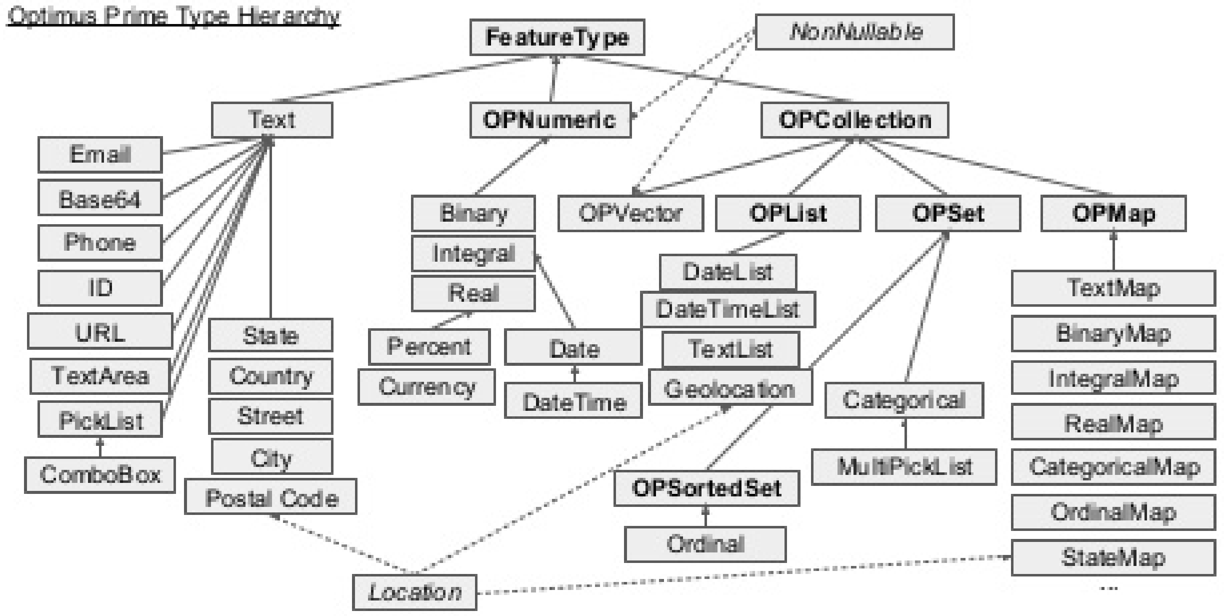
Legend: → - inheritance, **bold** - abstract class, *italic* - trait, normal - concrete class

Note: all the types are assumed to be nullable, unless NonNullable trait is mixed - https://developer.salesforce.com/docs/atlas.en-us.api.meta/api/field_types.htm

Take the types away!!

Why would we make this monstrosity??

- Sometimes a type is all you have
- Hierarchy allows both very specific and very general stages
- Type safety for production saves a lot of headaches



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Sanity Checking – the stage that checks your features

- Check data quality before modeling
- Label leakage
- Features have acceptable ranges
- The feature types allow much better checks

val *checkedVector* = *featureVector*.check(*survived*)

Model Selection Stage - Resampling, Hyper-parameter Tuning, Comparing Models

- Many possible models for each class of problem
- Many hyper parameters for each type of model
- Finding the right model for THIS dataset makes a huge difference

val (*pred, raw, prob*) = *checkedFeatureVector*.classify(*survived*)

Types can save us

And if you don't believe me take a look at the code

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```

```
def addFeatures(df: DataFrame): DataFrame = {
  // Create a new family size field := siblings + spouses + parents + children + self
  val familySizeUDF = udf { (sibsp: Double, parch: Double) => sibsp + parch + 1 }

  df.withColumn("fsize", familySizeUDF(col("sibsp"), col("parch"))) // <-- full freedom to overwrite
}

def fillMissing(df: DataFrame): DataFrame = {
  // Fill missing age values with average age
  val avgAge = df.select("age").agg(avg("age")).collect.first()

  // Fill missing embarked values with default "S" (i.e Southampton)
  val embarkedUDF = udf{(e: String)=> e match { case x if x == null || x.isEmpty => "S"; case x => x}}

  df.na.fill(Map("age" -> avgAge)).withColumn("embarked", embarkedUDF(col("embarked")))
}
```

Types can save us

And if you don’t believe me take a look at the code

```
// Modify the dataframe
val allData = fillMissing(addFeatures(rawData)).cache() // <-- need to remember about caching
// Split the data and cache it
val Array(trainSet, testSet) = allData.randomSplit(Array(0.75, 0.25)).map(_.cache())

// Prepare categorical columns
val categoricalFeatures = Array("pclass", "sex", "embarked")
val stringIndexers = categoricalFeatures.map(colName =>
  new StringIndexer().setInputCol(colName).setOutputCol(colName + "_index").fit(allData)
)

// Concat all the feature into a numeric feature vector
val allFeatures = Array("age", "sibsp", "parch", "fsize") ++ stringIndexers.map(_.getOutputCol)

val vectorAssembler = new VectorAssembler().setInputCols(allFeatures).setOutputCol("feature_vector”)

// Prepare Logistic Regression estimator
val logReg = new LogisticRegression().setFeaturesCol("feature_vector").setLabelCol("survived”)

// Finally build the pipeline with the stages above
val pipeline = new Pipeline().setStages(stringIndexers ++ Array(vectorAssembler, logReg))
```

Types can save us

And if you don't believe me take a look at the code

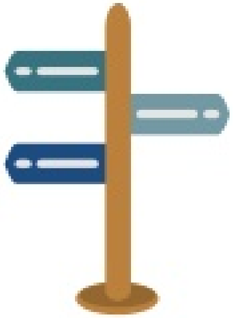
```scala
// Cross validate our pipeline with various parameters
val paramGrid =
  new ParamGridBuilder()
    .addGrid(logReg.regParam, Array(1, 0.1, 0.01))
    .addGrid(logReg.maxIter, Array(10, 50, 100))
    .build()

val crossValidator =
  new CrossValidator()
    .setEstimator(pipeline) // <-- set our pipeline here
    .setEstimatorParamMaps(paramGrid)
    .setEvaluator(new BinaryClassificationEvaluator().setLabelCol("survived"))
    .setNumFolds(3)

// Train the model & compute scores
val model: CrossValidationModel = crossValidator.fit(trainSet)
val scores: DataFrame = model.transform(testSet)

// Save the model for later use
model.save("/models/titanic-model.ml")
```

Where are we going and what have we learned

Key takeaways

- ML for B2B is a whole other beast
- Spark ML is great, but it needs type safety
- Simple and intuitive syntax saves you trouble down the road
- Types in ML are incredibly useful
- Scala has all the relevant facilities to provide the above
- Modularity and reusability is the key

Going forward with Optimus Prime



- Going beyond Spark ML for algorithms and small scale
- Making everything smarter (feature eng, sanity checking, model selection)
- Template generation
- Improvements to developer interface

If You're Curious ...

PredictionIO

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MetaMind

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Thank You