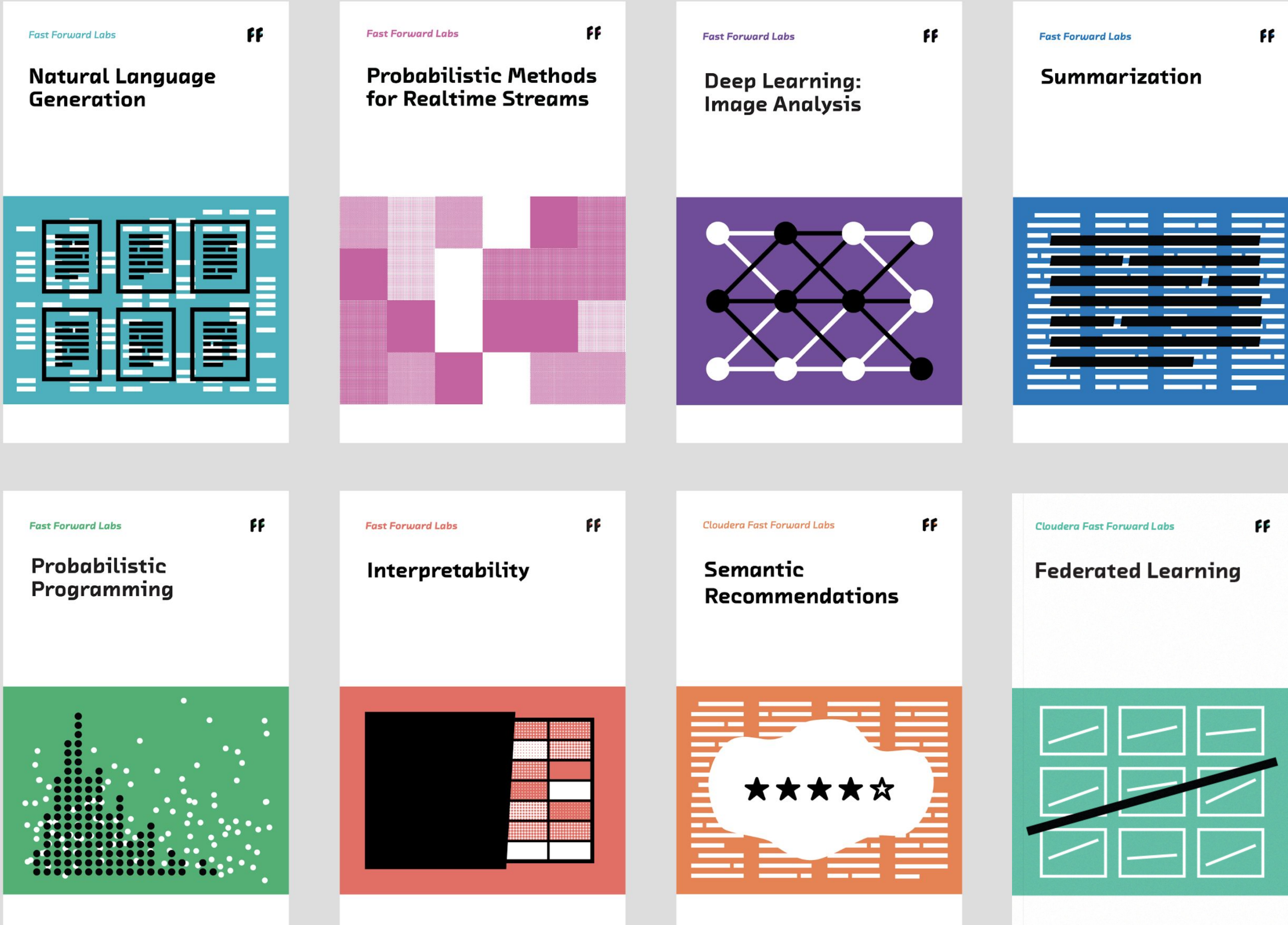
Data2Vis

Automatic Generation of Data Visualizations Using Sequence-to-Sequence Recurrent Neural Networks.

Victor Dibia
Research Engineer, Cloudera Fast Forward Labs

Çağatay Demiralp
Megagon Labs

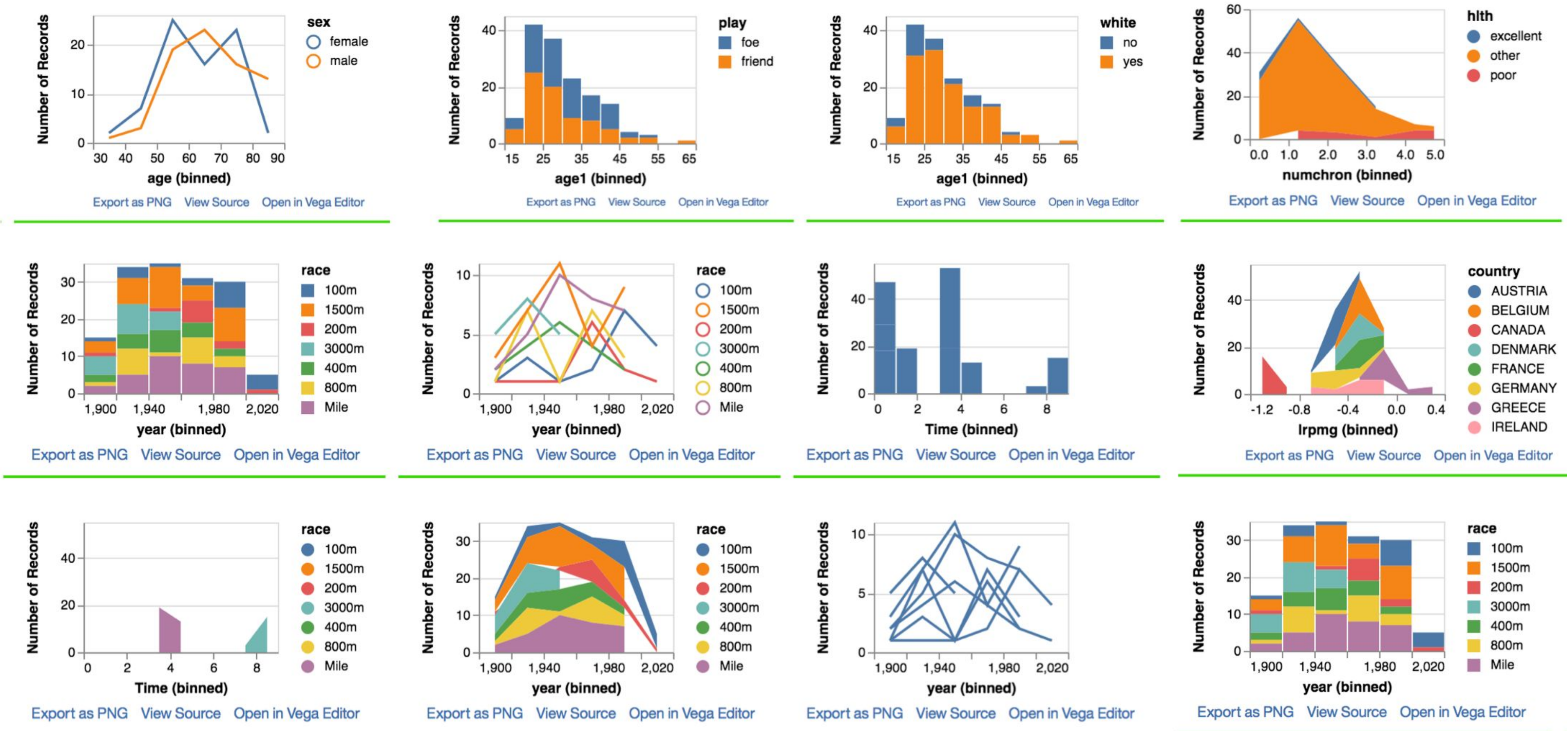
March 21, 2019


Fast Forward Labs
FF
Natural Language Generation
Fast Forward Labs
FF
Probabilistic Methods for Realtime Streams
Fast Forward Labs
FF
Deep Learning: Image Analysis
Fast Forward Labs
FF
Summarization
Fast Forward Labs
FF
Probabilistic Programming
Fast Forward Labs
FF
Interpretability
Cloudera Fast Forward Labs
FF
Semantic Recommendations
Cloudera Fast Forward Labs
FF
Federated Learning

Why Automate Visualizations?


Hint: We want to augment users (new capabilities, improved quality/speed).

Charts *can* make data more accessible



- Compared to tabular representations of data ..

- Reduced cognitive load
- Effective and expressive

Creating visualizations is

EFFORTFUL.

Visualization authoring is effortful

1 Hypothesis	2 Visual Encoding	3 Implementation (code)

- Generating hypothesis and questions regarding data.
- Identifying appropriate visual encoding strategies (chart type, data transformations etc.) that support hypothesis.
- Writing code to implement visualizations

Visualization authoring is effortful

1 Hypothesis	2 Visual Encoding	3 Implementation (code)

Effective visual encoding and implementation can be challenging for novice users.

- Many (novice) users lack the skills to select appropriate visual encodings and to write code that implement visualizations.
- Automated approaches can help (augment) with tasks 2 and 3.

More so ..

Visualization Recommendation
(CompassQL, Voyager 2, VizML)

Visualization Ranking
(VizDeck, Draco, Deep Eye)

- Existing approaches to automated viz are **limited.**
  - Depend on **heuristics** and **hand engineered features** which need to be manually updated.
  - Does not leverage knowledge codified within **existing** visualization examples.

A Scalable, learning based approach?

Data2Vis a (deep) learning based approach to automated visualization

Approach

- Formulate visualization authoring as a machine learning problem.
- Identify data sampling strategies that enable training with (limited) data
- Design metrics that enable evaluation of models
- Present a model that learns to map raw data to generated visualizations.
- Declare that we have solved AGI.

Related Work

Automated Visualization Tools

Automated Visualization

Voyager2

Wongsuphasawat et al 2016

Recommend visualizations based on partial specifications provided by users.

Recommend univariate and bivariate plots based on a set of enumerated heuristics.

Draco

Moritz et al 2018

Modeling visualization design knowledge as a collection of constraints, learn weights for soft constraints from experimental data.

Deep Eye

Luo et al 2018

Uses learned binary classifier + learning to rank algorithms to rank visualizations as “Good or Bad” based on examples.

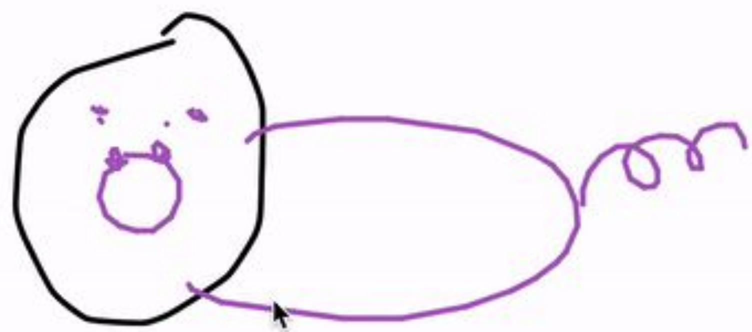
VizML

Hu et al 2018

Train a model to predict *parts* of visualization specifications - visual encoding choices (x,y axis) - using hand engineered features.

Neural Synthesis Models

DNNs for Neural Synthesis



Sketch RNN (Ha et al, 2017)

DNNs for Neural Synthesis

Models that learn human-like creative processes.

- **SketchRNN: Generate Stroke based drawings for common objects** (Ha et al 2017)
- **Text to image synthesis.** (Reed et al 2016)
- **Google Smart Compose and Smart Reply** (Kannan et al 2016)

Code Generation Models

DNNs for Code Generation

Models that learn to generate code.

- **Domain Specific Language Translation** (Yin et al 2017, Zhong et al, 2017)
- **Natural Language to SQL** (Dong & Lapata 2016, Zhong et al, 2017)
- **TCG (trading card games) to Python and Java Language specification.** (Ling et al 2016)

Table: CFLDraft

Pick #	CFL Team	Player	Position	College
27	Hamilton Tiger-Cats	Connor Healy	DB	Wilfrid Laurier
28	Calgary Stampeders	Anthony Forgone	OL	York
29	Ottawa Renegades	L.P. Ladouceur	DT	California
30	Toronto Argonauts	Frank Hoffman	DL	York
...	...	...	...	...

Question:

How many CFL teams are from York College?

SQL:

```
SELECT COUNT CFL Team FROM
CFLDraft WHERE College = "York"
```

Result:

2

Neural Machine Translation Models

DNNs for Machine Translation

- **Family of Encoder-Decoder Models that learn mappings from an input sequence to an output sequence.** (Britz et al 2017)
- **Frequently referred to as Seq2Seq models, but have applications for <u>non-sequential</u> problems e.g.** Image Captioning, Text Summarization, Code Generation.
- **Non-sequential applications are enabled by <u>Bi-Directional RNNs</u> and <u>Attention Mechanisms</u>**

DNNs for Machine Translation

BiDirectional RNNs

- Consists of both a **forward RNN** (reads input sequence and calculates forward hidden states) and a **backward RNN** (reads input sequence in reverse order and calculates backward hidden states). (Shuster et al 1997).
- Generates an hidden state that is a concatenation of both forward and backward RNNs.

DNNs for Machine Translation

Attention Mechanism

Allows a model to focus on aspects of an input sequence while generating output tokens

- Makes translation models robust to performance degradation while generating lengthy sequences.
- Enables the learning of mappings between source and target sequences of different lengths.
- Allows for interpretability explorations.

Model

Problem Formulation

Data	**Visualization Specification**
Input data in JSON | { "country": "AUS", "il": "0.058" ..}	Vega Lite Spec | { "y": {"field":"gender", "type": ..}

- Formulate as a **neural translation problem** (sequence to sequence models).
- Learn mappings from raw data to visualization specification in an End-to-End trainable task.

Model Input

Data
Input data in JSON | { "country": "AUS", "il": "0.058" ..}

Visualization Specification
Vega Lite Spec | { "y": {"field":"gender", "type": ..}

Model Input

JSON Data
(Non-nested)

[{"Time":"152","size":"4.51","treat":"ozone","tree":"1"},{"Time":"174","size":"4.98","treat":"ozone","tree":"1"},{"Time":"201","size":"5.41","treat":"ozone","tree":"1"},{"Time":"227","size":"5.9","treat":"ozone","tree":"1"},{"Time":"258","size":"6.15","treat":"ozone","tree":"1"},{"Time":"152","size":"4.24","treat":"ozone","tree":"2"},{"Time":"174","size":"4.2","treat":"ozone","tree":"2"},{"Time":"201","size":"4.68","treat":"ozone","tree":"2"},{"Time":"227","size":"4.92","treat":"ozone","tree":"2"},{"Time":"258","size":"4.96","treat":"ozone","tree":"2"},{"Time":"152","size":"3.98","treat":"ozone","tree":"3"},{"Time":"174","size":"4.36","treat":"ozone","tree":"3"},{"Time":"201","size":"4.79","treat":"ozone","tree":"3"},{"Time":"227","size":"4.99","treat":"ozone","tree":"3"},{"Time":"258","size":"5.03","treat":"ozone","tree":"3"},{"Time":"152","size":"4.36","treat":"ozone","tree":"4"}]

Model Output

Data
Input data in JSON | { "country": "AUS", "il": "0.058” ..}

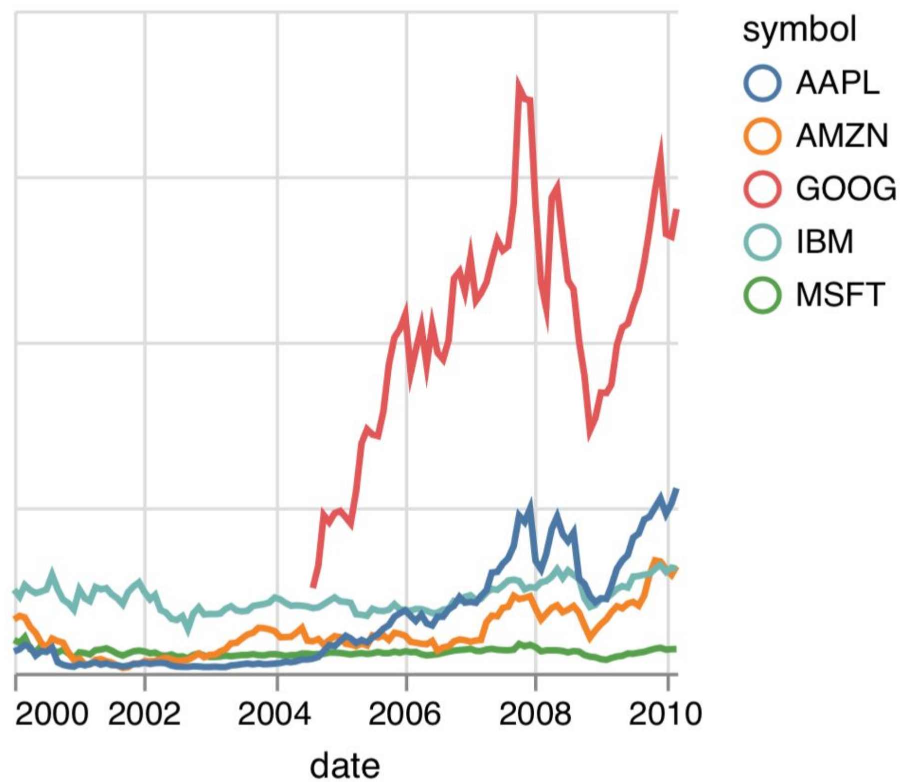
Visualization Specification
Vega Lite Spec | { ”y": {”field”:”gender”, ”type”: ..}

Model Output

Vega Lite

JSON specification.

```
{
  "data": {
    "url": "data/stocks.csv"},
  "mark": "line",
  "encoding": {
    "x": {
      "field": "date",
      "type": "temporal",
      "axis": {
        "format": "%Y" }
    },
    "y": {
      "field": "price",
      "type": "quantitative" },
    "color": {
      "field": "symbol",
      "type": "nominal" }
  }
}
```



Mapping

Data
Input data in JSON | { "country": "AUS", "il": "0.058" ..}

Visualization Specification
Vega Lite Spec | { "y": {"field":"gender", "type": ..}

[{"Time":"1992","size":"4.51","treat":"ozone","tree":"1"}
...
...
...
,{"Time":"1993","size":"4.98","treat":"ozone","tree":"1"}]

→

{"encoding": {"detail": {"type": "temporal", "timeUnit": "week", "field": "Time"}, "x": {"type": "quantitative", "field": "size", "bin": true}, "y": {"aggregate": "count", "field": "*", "type": "quantitative"}}, "mark": "area"}

Training Data

- **4300 Vega Lite specifications based on 11 datasets generated using CompassQL** (Poco et al 2017)**.**

- **CompassQL is based on**
  - **Heuristics and rules which enumerate cluster and rank visualizations according to known data properties and perceptual considerations.**
  - **Filtered manually to remove problematic instances**
  - **1-3 variables per chart, multiple chart types.**
  - **“MNIST” for automated visualization experimenbts**

Sampling strategy

- **Repetitive sampling of datum to visualization.**

- **Training data is generated by sampling examples**
  - **Training pair consists of single row from dataset (JSON) and visualization specification (JSON)**
  - **50 random pairs selected from each example**
  - **Data normalized** (replace field names with normalized values e.g. str0, str1, num0, num1)
  - **215k pairs after sampling**

Training Data Pair

Data
Input data in JSON | { "country": "AUS", "il": "0.058” ..}

Visualization Specification
Vega Lite Spec | { ”y": {”field”:”gender”, ”type”: ..}

{"Time":"1993","size":"4.51","treat":"ozone","tree":"1"}

→

{"encoding": {"detail": {"type": "temporal", "timeUnit": "week", "field": "Time"}, "x": {"type": "quantitative", "field": "size", "bin": true}, "y": {"aggregate": "count", "field": "*", "type": "quantitative"}}, "mark": "area"}

Training Data Transformation

Data	**Visualization Specification**
Input data in JSON | { "country": "AUS", "il": "0.058" ..}	Vega Lite Spec | { "y": {"field":"gender", "type": ..}

- **We apply transformations to the data, replace numeric, string and date fields with short forms num0, str0, dt0.**

{"dt0":"152","num0":"4.51","str0":"ozone","num1":"1"}

→

{"encoding": {"detail": {"type": "temporal", "timeUnit": "week", "field": "dt0"}, "x": {"type": "quantitative", "field": "size", "bin": true}, "y": {"aggregate": "count", "field": "*", "type": "quantitative"}}, "mark": "area"}

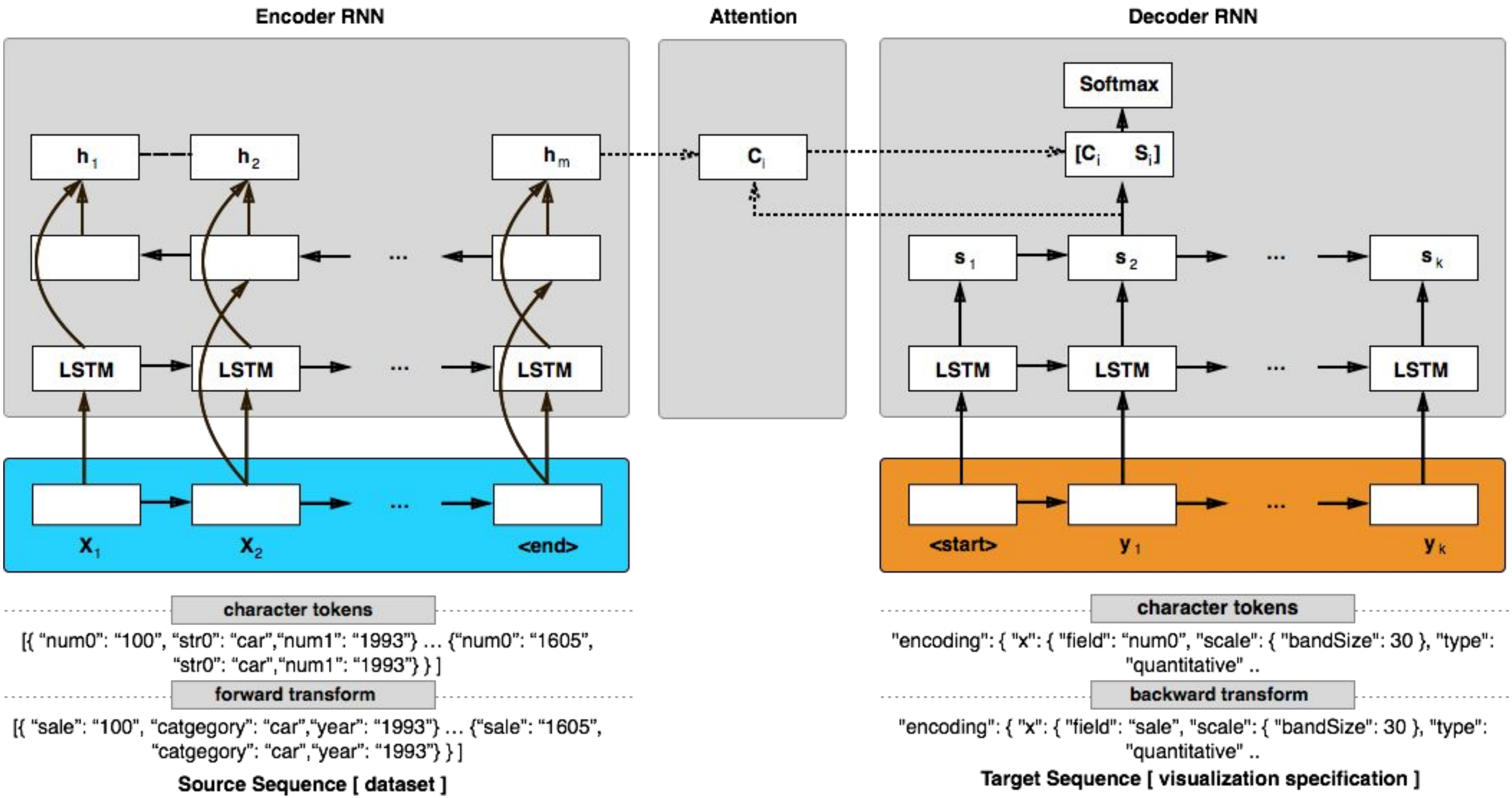
Training Data Transformation

Data	**Visualization Specification**
Input data in JSON | { "country": "AUS", "il": "0.058" ..}	Vega Lite Spec | { "y": {"field":"gender", "type": ..}

- **We apply transformations to the data, replace numeric, string and date fields with short forms num0, str0, dt0.**

- **Transformation provides following benefits**
  - Reduce overall vocabulary size
  - Prevent LSTMs from learning specific field names
  - Reduce overall sequence length (faster training, less memory)

Model



Encoder/Decoder Model

Model based on architecture by Britz et al 2017

Model Training

- Character tokenization strategy
- Dropout Rate of 0.5
- Fixed learning rate (0.0001)
- Adam optimizer
- 20,000 steps
- Final log perplexity of 0.032
- Maximum seq length of 500

The training code is based on the Google Seq2Seq implementation (Britz et al 2017)

CLOUDERA DATA SCIENCE WORKBENCH

Accelerate Machine Learning from Research to Production

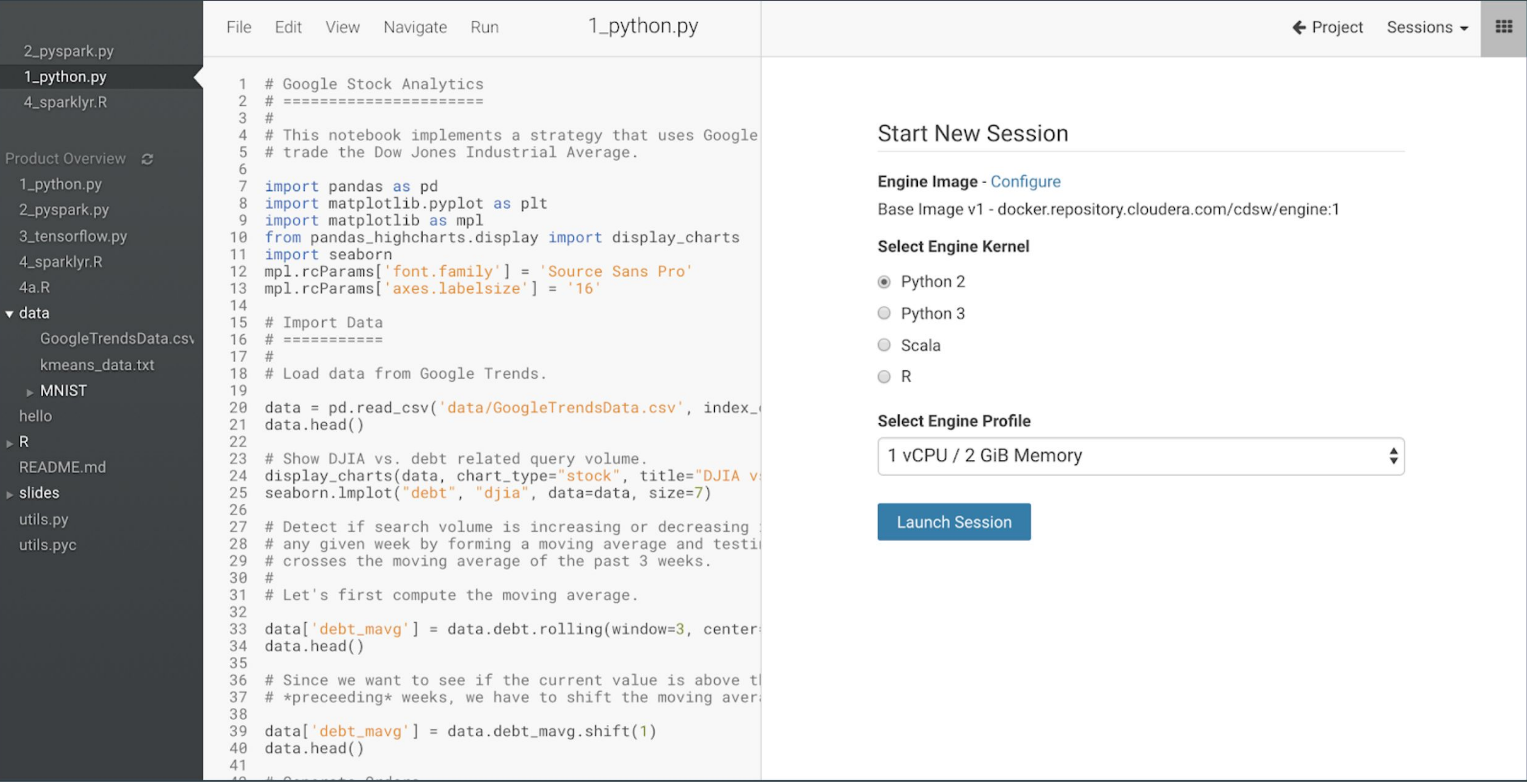
For data scientists

- Experiment faster
  Use R, Python, or Scala with on-demand compute and secure CDH data access
- Work together
  Share reproducible research with your whole team
- Deploy with confidence
  Get to production repeatably and without recoding

For IT professionals

- Bring data science to the data
  Give your data science team more freedom while reducing the risk and cost of silos
- Secure by default
  Leverage common security and governance across workloads
- Run anywhere
  On-premises or in the cloud

© Cloudera, Inc. All rights reserved.



- **Docker/Kubernetes based**
- **Analyze your data**
- **Train models (run, track, compare)**
- **Deploy APIs**
- **Multi tenant, collaborative, secure**

Evaluation

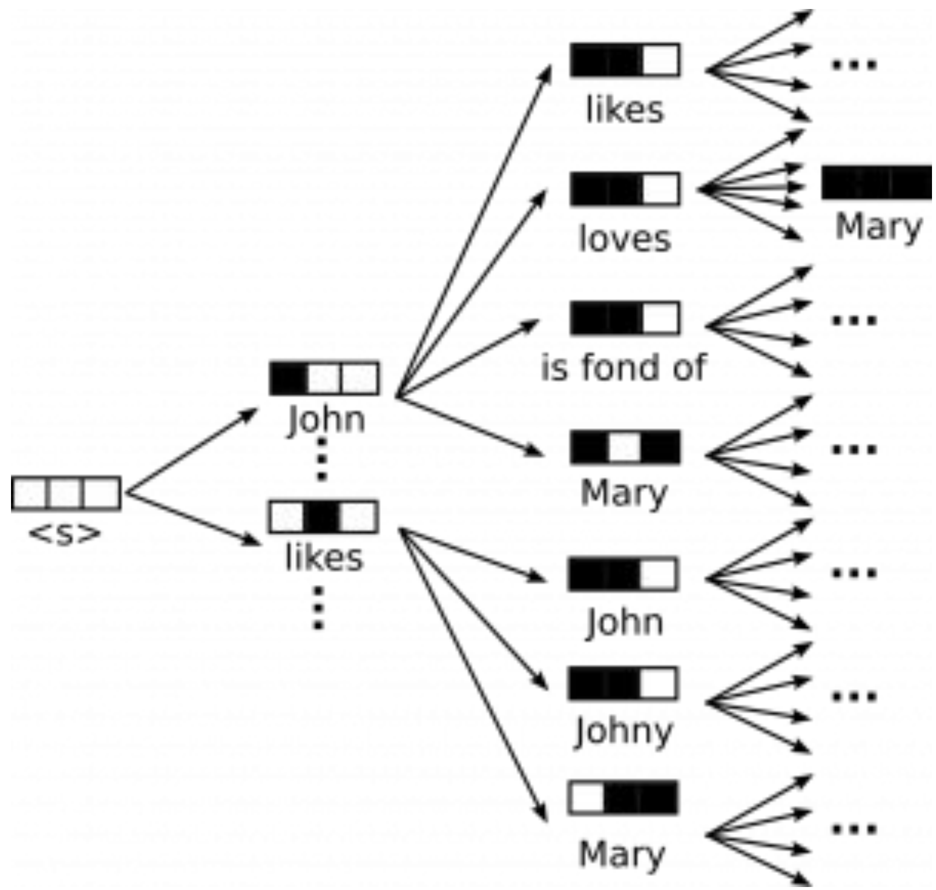
Model Evaluation

- **Diagnostic Metrics**
  - **Language Syntax Validity**
    A measure of how well the model learns the rules of the visualization language (JSON).
    % of all generated examples that are **valid JSON**
  - **Grammar Syntax Validity**
    A measure of how well the model learns the visualization grammar (Vega Lite).
    % of all generated examples that ***compile*** **in Vega Lite**.

Beam Search Decoding

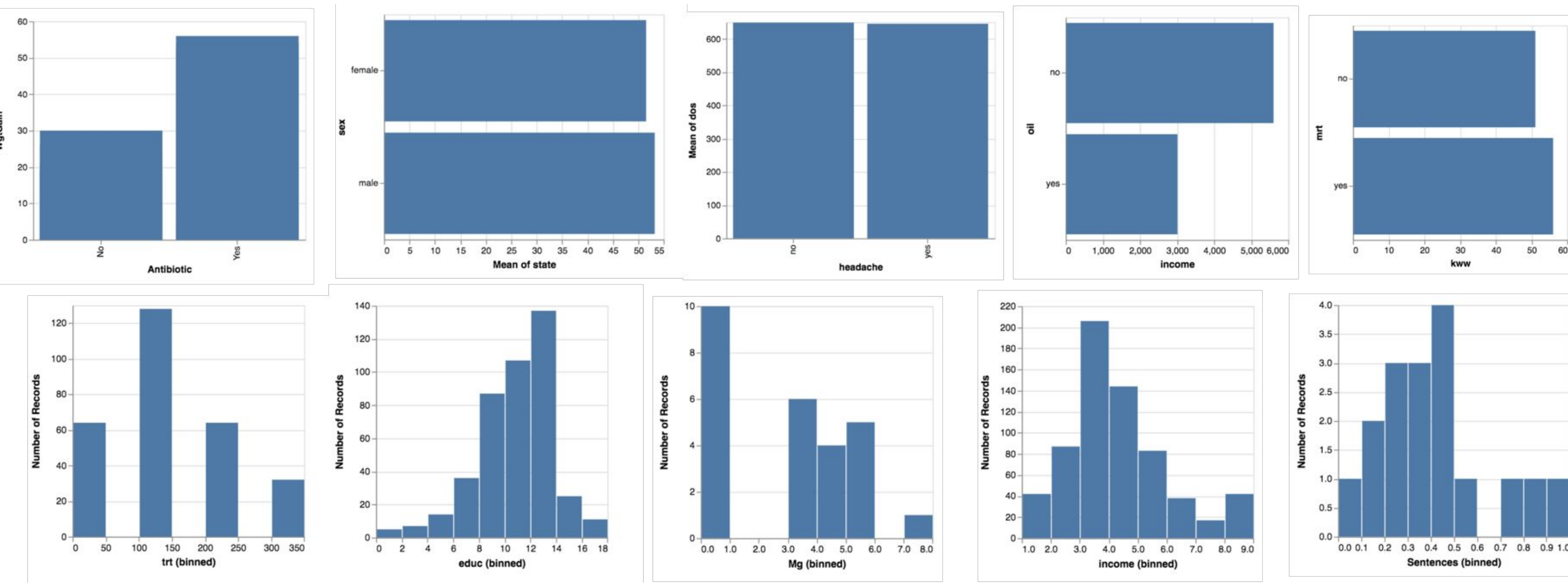
- Expands all possible next steps and keeps the k most likely, where k is a user-specified parameter.

- We leverage beam search in generating diverse specifications based on same data.



Qualitative Results

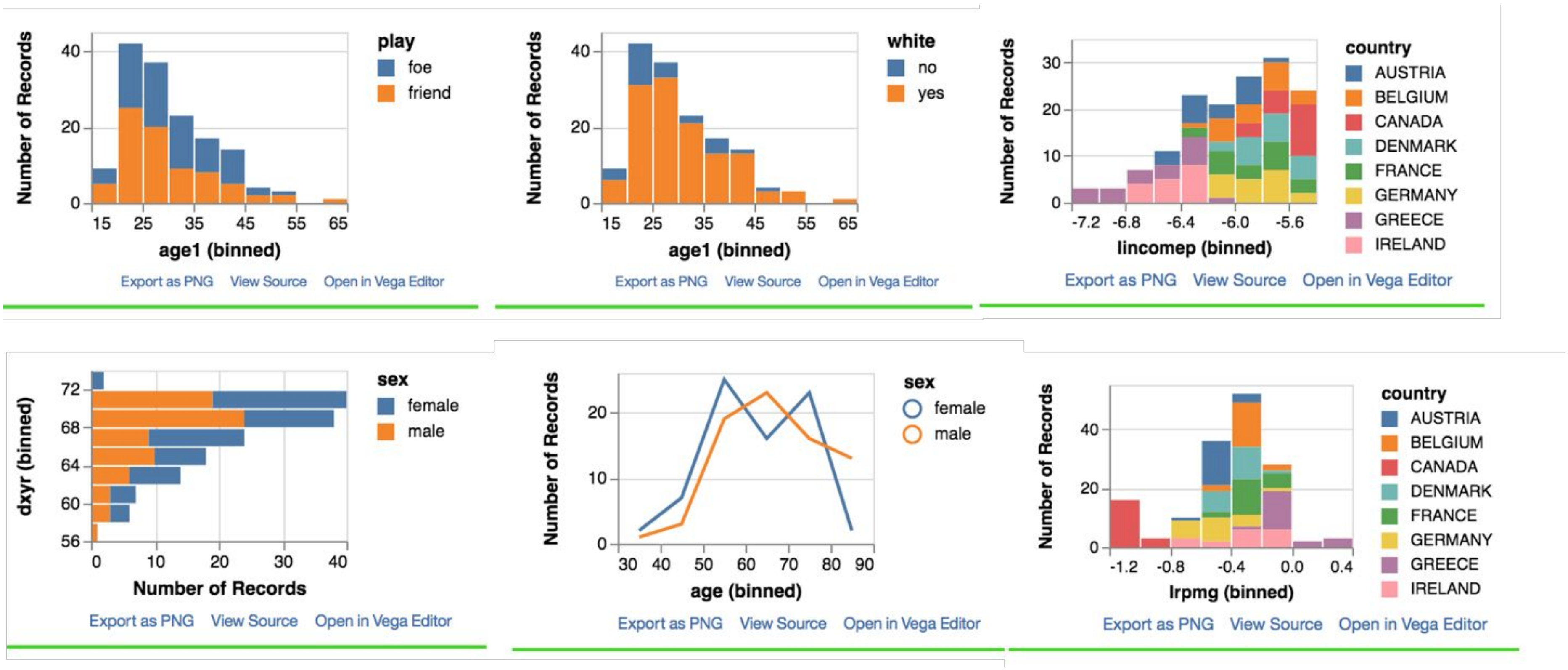
Model learns to generate multivariate and bivariate plots



Model is shown random data from the Rdataset collection not used in training.

Qualitative Results

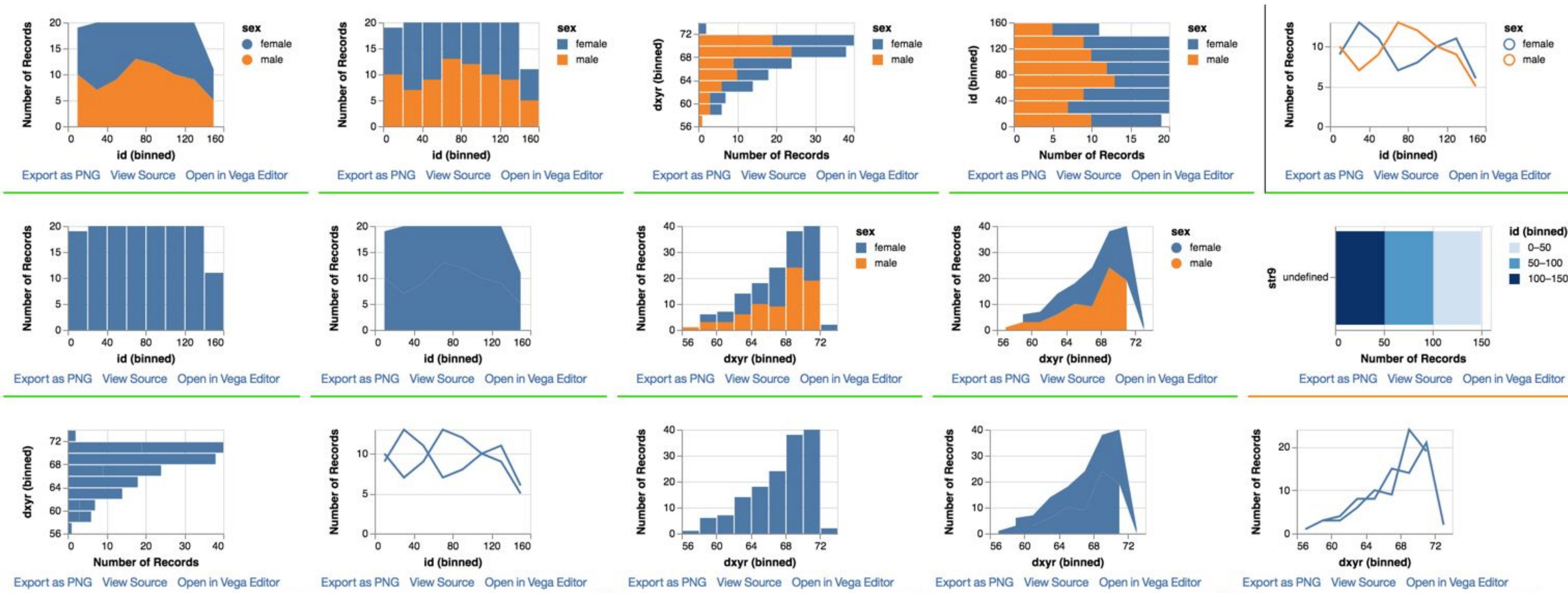
Model learns to perform selections using categorical fields (yes/no, male/female, state, country etc.)



Model is shown random data from the Rdataset collection not used in training.

Qualitative Results

Beam search decoding (k=15) generates diverse chart types (bar, area, line)



Model is shown random data from the Rdataset collection not used in training.

Quantitative Evaluation

- **Evaluation Metrics**
  - We train 3 models -
    - No attention (Bidirectional),
    - Attention (Unidirectional),
    - Attention (Bidirectional)
  - Test each model with various values for beam width k (5, 10, 15).
  - Compute mean metric for 100 randomly selected datasets from the Rdataset collection.

Quantitative Evaluation

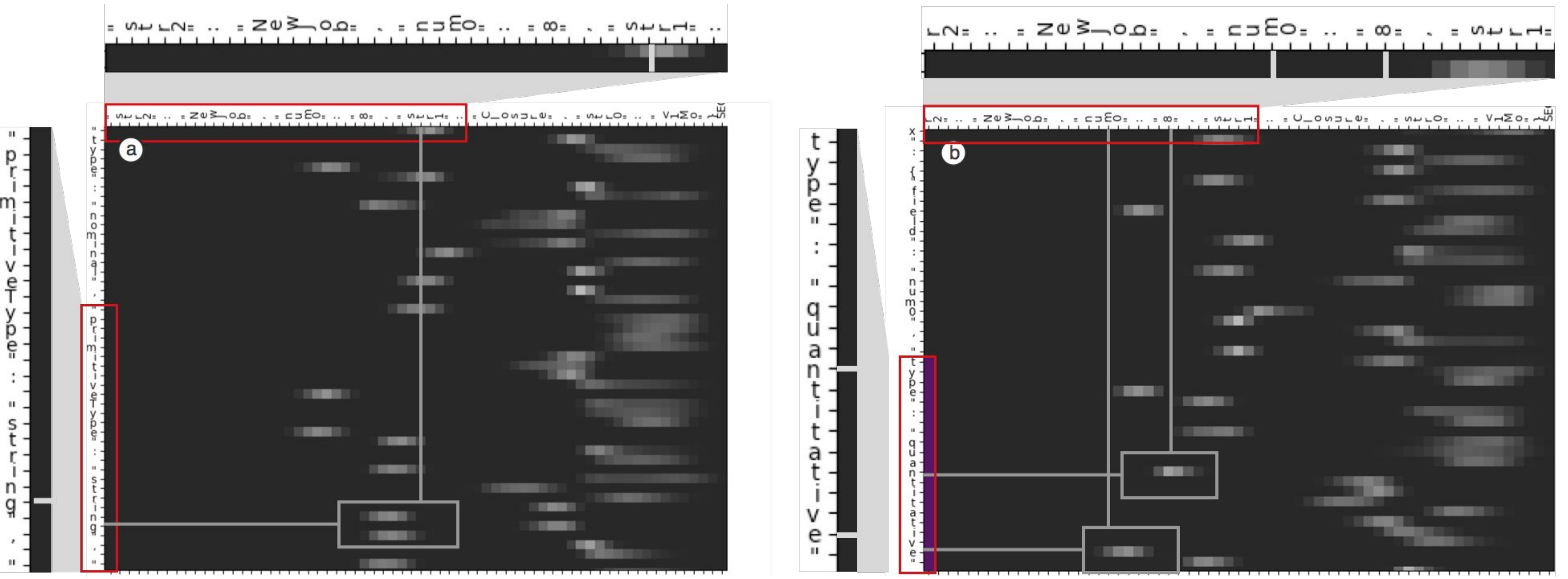
- **Evaluation Metrics**

	Beam width (k=5)			Beam width (k=10)			Beam width (k=15)			Beam width (k=20)		
	No Attn	**Attn**		**No Attn**	**Attn**		**No Attn**	**Attn**		**No Attn**	**Attn**	
	bi	**uni**	**bi**	**bi**	**uni**	**bi**	**bi**	**uni**	**bi**	**bi**	**uni**	**bi**
Language Validity	0.96	0.892	0.826	0.937	0.898	0.897	0.967	0.76	0.901	0.97	0.838	0.878
Grammar Validity	0.304	0.772	0.824	0.487	0.898	0.897	0.628	0.696	**0.902**	0.63	0.813	0.878

- All models learn to generate valid JSON syntax.
- Bidrectional models perform better than unidirectional models on both metrics on the average.
- Attention based models do significantly better on Grammar metric.
- Attention based BiDirectional Models (with beam width **k=15**) have the best performance for generating valid “plotable” Vega Lite specifications.

Attention Plots

Attention plots show the model learns to pay attention to input data in generating aspects of visualization specification



Example attention plots for a visualization generation case (a) Model learns to pay attention to field name "str" in generating the "string" field type applied to the field. (b) Model learns to pay attention to the field name "num0" and its value in specifying the "quantitative" field type applied to the field

Summary

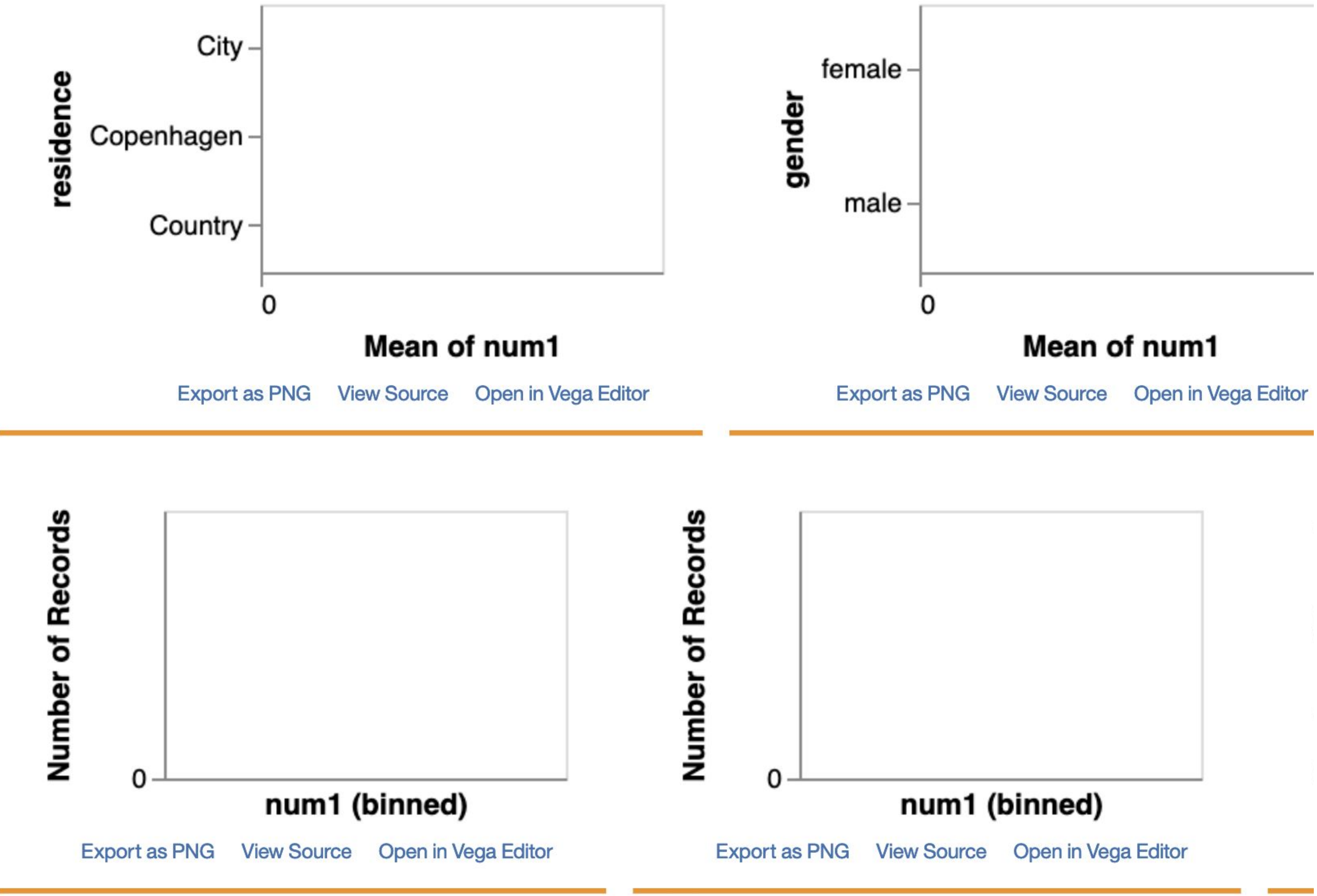
- **Limited Training Data**
  Our current dataset, while sufficient for demonstrating the viability of our approach, has limited coverage of real world use cases.

- **Phantom Fields**
  In 10~20% of cases, the model generates specifications with fields not in the dataset. In practice we can detect this at runtime and keep exploring beam search generation until valid specs are generated.

Evaluation

Limitations

- **Training Data**
  Our current dataset, while sufficient for demonstrating the viability of our approach, has limited coverage of real world use cases.
- **Conditioned Generation**
  Current model does not support conditioned visualization generation.
- **Phantom Fields**
  In 10~20% of cases, the model generates specifications with fields not in the dataset. In practice we can detect this at runtime and keep exploring beam search generation until valid specs are generated.



- **Ofcourse …** there are failure cases!

Future Work

- **Additional Data Collection.**
  Curating a more diverse dataset that enables training a more robust model.
- **Extending Data2Vis to Generate Multiple Plausible Visualizations.**
  Explore approaches (e.g. conditioned GANs or VAEs) to train a model that generates multiple valid visualizations with specified conditions.
- **Targeting Additional Grammars**
  Training models that map input data to multiple different visualization specification languages (e.g. Vega, ggplot2, D3 etc.).
- **Natural Language and Visualization Specification**
  Training models that generate visualizations based on natural language text and input data.
- **Browser deployment**
  Javascript library that provides fast generation in the browser.

Summary

Formulating data visualization as a sequence to sequence problem works well. The following insights were useful.

- Transformations which scaffold the learning process.
- Bidirectional RNNs which significantly enable learning complex non-sequential mappings.
- Repetitive sampling and beam search decoding for multiple visualization generation.

Contributions

- Formulate automated visualization as a neural translation problem (map data to visualization specifications)
- End-to-End trainable model for visualization generation
- Training strategy (data generation, transformations etc.)
- Metrics for evaluating End-to-End visualization generation systems
- Sample code and demo

https://github.com/victordibia/data2vis

Code and Trained Model

Github:
https://github.com/victordibia/data2vis

Paper:
https://arxiv.org/abs/1804.03126

Thanks.

Victor Dibia
victor.dibia@gmail.com