

Towards a Paradigm for Visual Modeling

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I. SOTA & Philosophy

| Visualization & ML

Visualization recently gained a foothold in the field of AI research.

Typically, work focuses on visualizing modules or specific dynamics of ML models for:

- debugging
- explainability or interpretability
- pedagogy

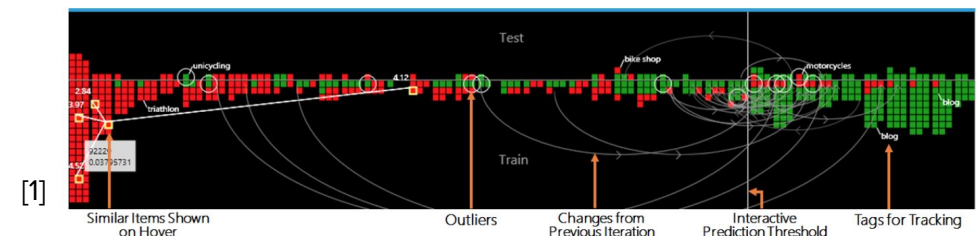
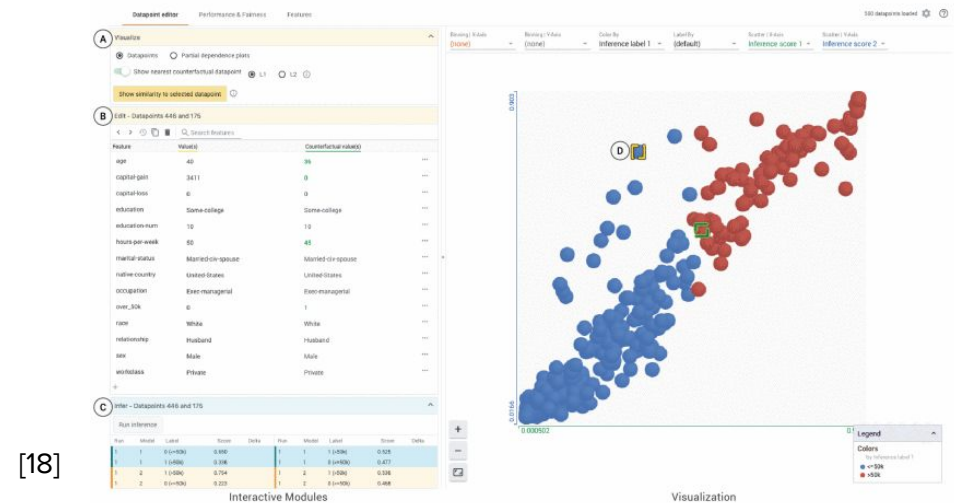
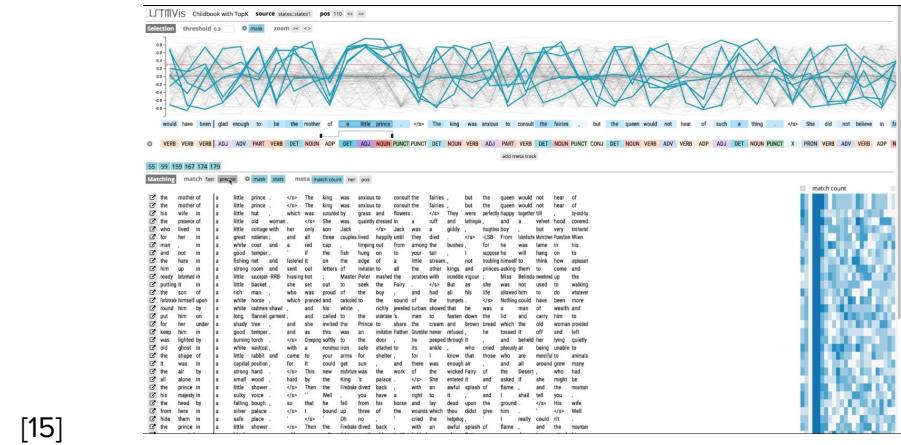
“Auto-ML” platforms have also emerged, focused on machine-assisted model workflows so ML solutions can be easily leveraged for common problems.

Explainable AI

A host of recent efforts have been focused on model debugging, interpretability and explainability.

- Tracing the activations across an unfolded RNN or LSTM for a given input.
- Attention mechanisms highlight aspects of training or prediction to help with interpretation.
- Visualizing image activations at various CNN network layers.
- Allowing for real-time experimentation or 'what-ifs' by changing input data features and execution parameters.
- Linking classified data samples in terms of prediction.

Focus is typically on a single model, interrogating its training and prediction dynamics. Model is taken to have been assembled externally, and these visualizations are for experimentation or debugging.

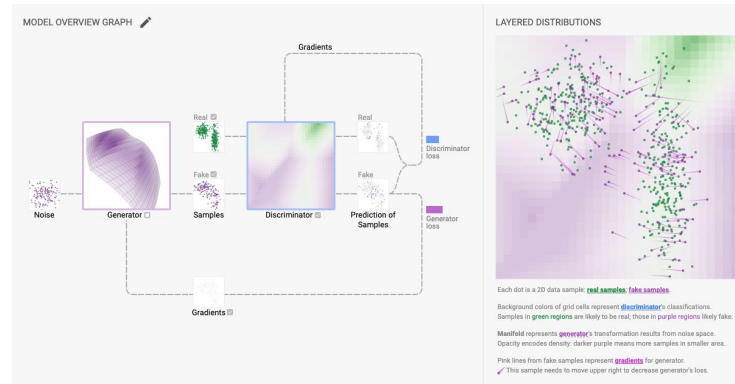


Pedagogy

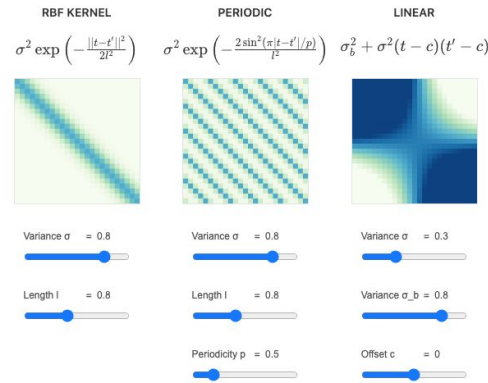
Similar focus of various interactive tutorials and ML ‘playgrounds’.

Pedagogical resources to understand core ideas and visualize complex data transformations and training dynamics.

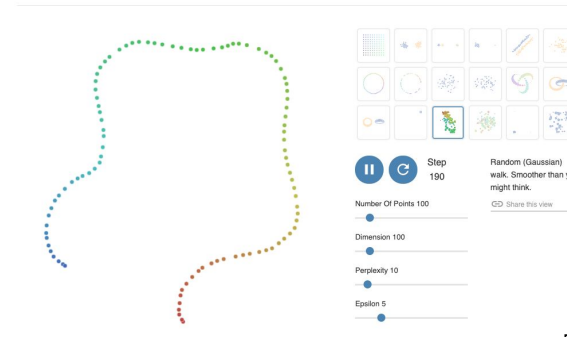
Interactive features allow users to explore input and parameter space within some predefined intervals to see outcomes



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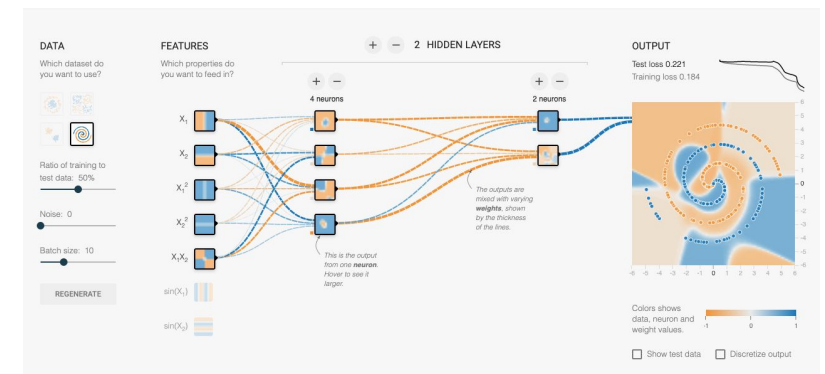


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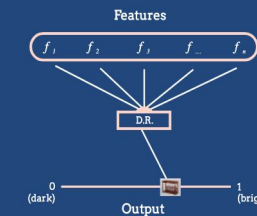


Projecting onto a line

These features can be thought of as vectors existing in a high-dimensional space. Visualizing the vectors would reveal a lot about the distribution of the data, however humans can't see so many dimensions all at once.

Instead the data can be projected onto a lower dimension, one that can be visualized directly. This kind of projection is called an *embedding*.

Computing a 1-dimensional embedding requires taking each artwork and computing a single number to describe it. A benefit of reducing to 1D is that the numbers, and the artworks, can be sorted on a line.



On the right you see the artwork positioned according to their *average pixel brightness*. Notice that the images are sorted, with the darkest images appearing at the top and the brightest images on the bottom!

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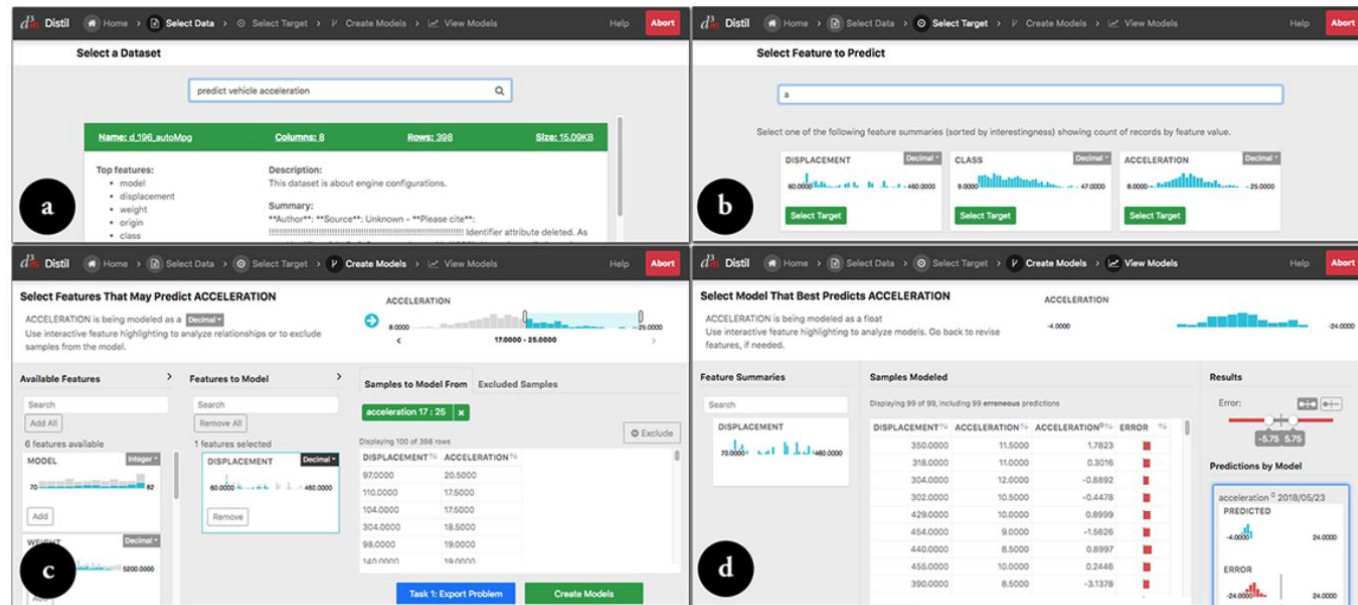
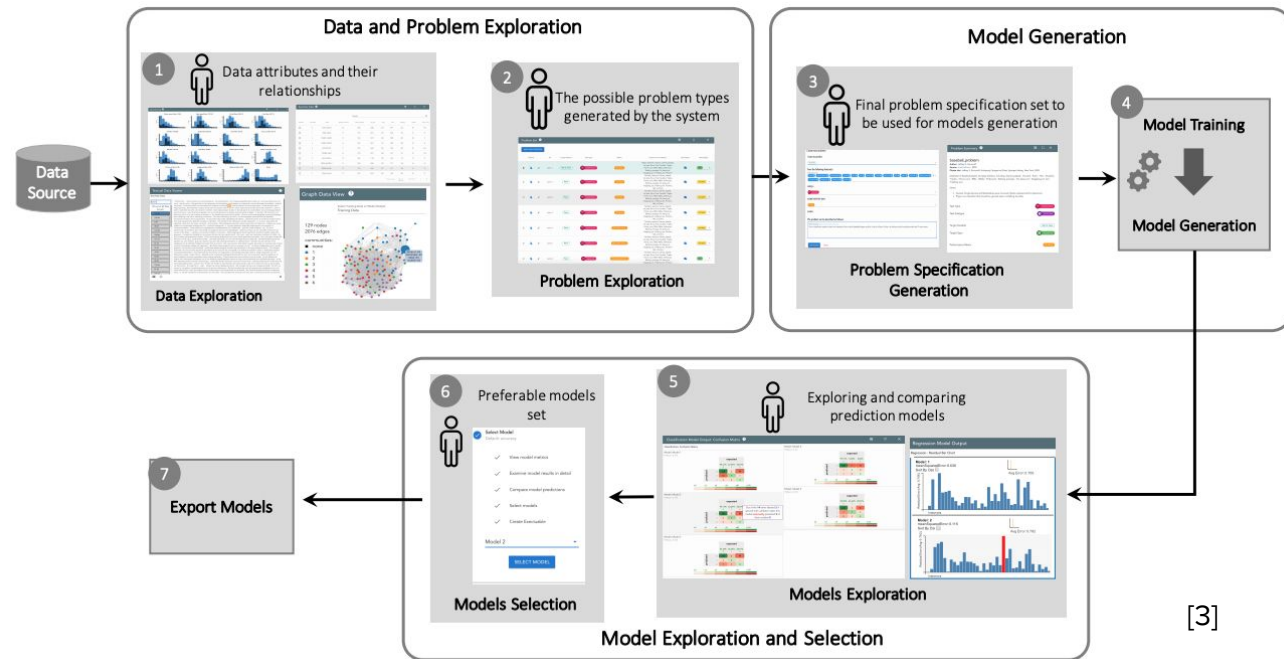
AutoML interfaces

Larger AutoML systems are emerging that look to streamline the full ML workflow from ingesting input data to model inference.

Geared towards enabling non-experts to use ML tools or accelerating some work by ML practitioners.

Typically focused on common industry problems (classification, clustering, linear models).

Sometimes remain in an awkward place: either users of AutoML systems still need ML knowledge for model selection, training, parameter optimization; or these choices are entirely black-boxed away.



[13]

[3]

Visual Modeling & Augmented Intelligence

Artificial intelligence, as often benchmarked against human intelligence, attempts to replicate human skill. It is better understood as a geometric intelligence: it has an entirely different, non-embodied ontology, lacks intuition and creativity, struggles with generalization and synthetical understanding. Has near-perfect memory and recall, calculation capability, pattern detection at inhuman scale.

Augmented intelligence is a historical concept dating back to Doug Engelbert and JCR Licklieter. Core emphasis is on the human-in-the-loop, where human and machine intelligence serve to augment each other in real time, interactively, in a human-machine interface. Not trying to replicate human skill in a machine; but technologically amplify human skill.

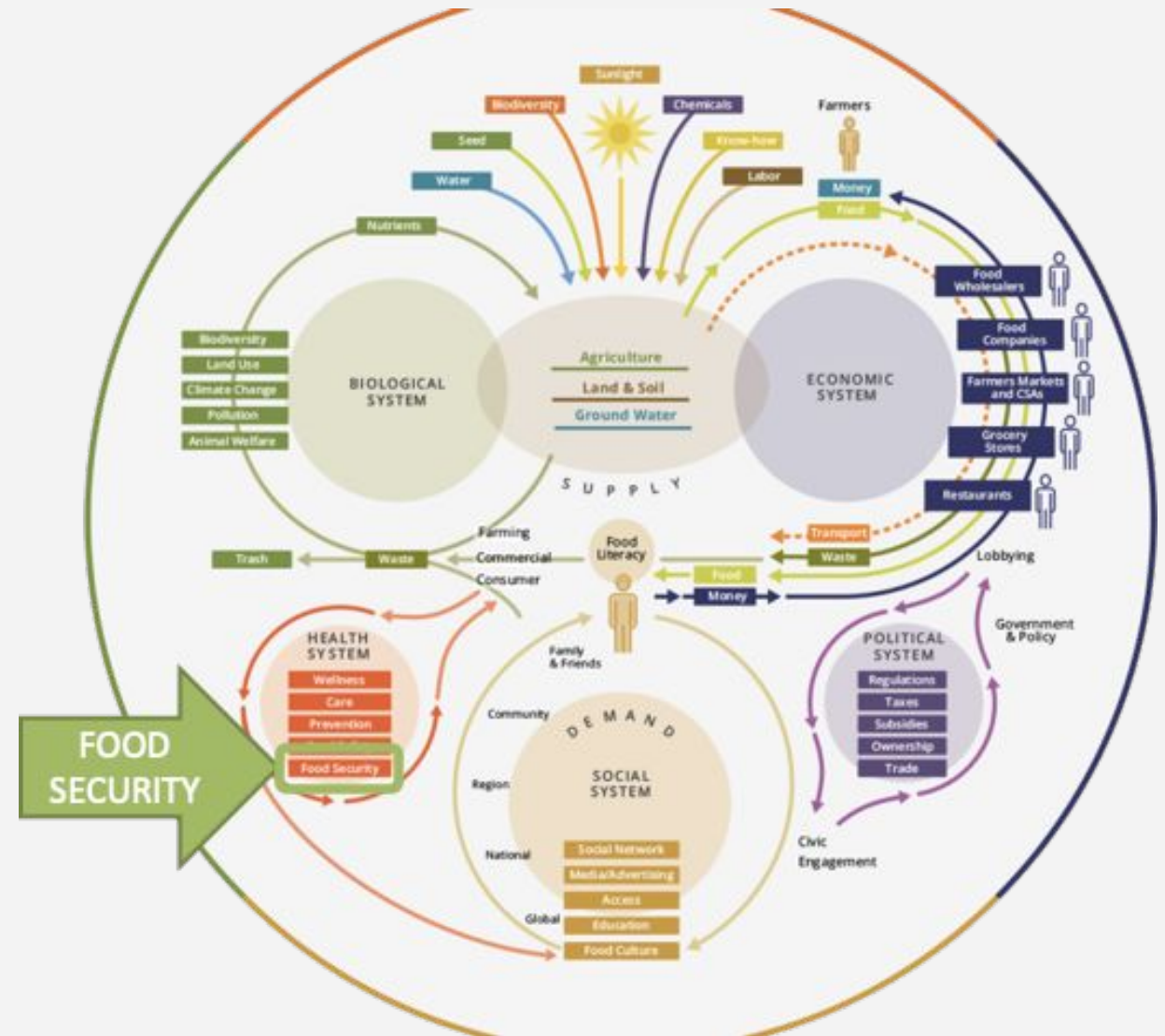
Hypothesis is that (while we wait for AGI) augmented intelligence is the paradigm to follow today for large-scale systems attempting to solve compositional problems (not end-to-end learning tasks such as translation, vision, etc).

Visual modeling as explored here is cast as a form of augmented intelligence.

II. Research Efforts in DARPA Programs

World Modelers (WM)

- DARPA program aiming to model socio-natural complex systems such as drought, famine, food security [4].
- Unsolved multi-domain, multi-resolution problem.
- Involving systems of systems, with intricate linkages and causal dynamics.
- Problem has both qualitative and quantitative dimensions and types of information, with large stores of data and knowledge artifacts.
- Current computational models in the space typically siloed in their domains (agricultural yield, political instability, disease spread, rainfall estimates, flood prediction).



World Modelers

Scenario(s):

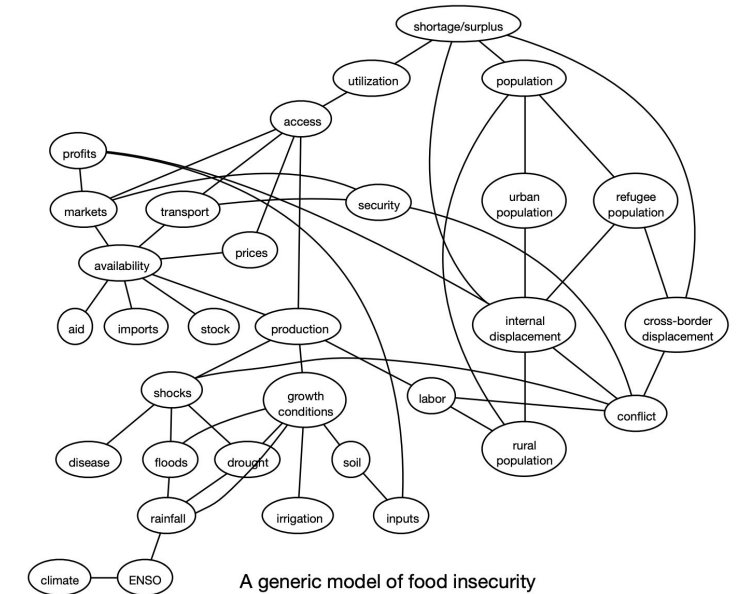
- Emergency response: famine event has occurred; aid is required.
- Forecasting dynamics: rain is predicted to be below average - which areas will be hardest hit? What other consequences will result?
- System awareness: decision-maker needs a briefing on main drivers of food insecurity, and linked causal factors and impacts.
- Multi-domain analysis is required, as use-cases shift quite drastically (for e.g. locusts, conflict).

Current status:

- Takes months to assemble data; scour literature for new factors; build and test models; make predictions; capture them in artifacts; present to decision maker; deliberate over policy; execute policy; engage logistics network to deliver aid or provide support.

Need to enable:

- Exploration of networks of factors and knowledge hypotheses in literature at large.
- Access to disparate data from expert models and open-source indicators.
- Quick assembly of models of complex systems, compare / contrast alternatives.
- Intervention analysis to experiment with causal dynamics.
- Adaptation to new domains as necessary.
- Summary artifacts for downstream decision-makers.



A generic model of food insecurity

[5]

- o Step 1: Generate or retrieve a *generic* qualitative, causal food security model;
- o Step 2: Modify the model for the specific analyses of Southern Sudan;
- o Step 3: Build workflows of expert, quantitative models, where available;
- o Step 4: Parameterize quantitative models and the qualitative, causal model;
- o Step 5: Configure scenarios and run analyses, producing quantitative results for factors of interest (e.g., food prices, calorie intake);
- o Step 6: Produce an “uncertainty report” that documents sources of uncertainty, run uncertainty-reduction procedures and sensitivity analyses;
- o Step 7: Identify possible actions to affect factors of interest (e.g., peacekeepers at markets).

Platform: Causemos

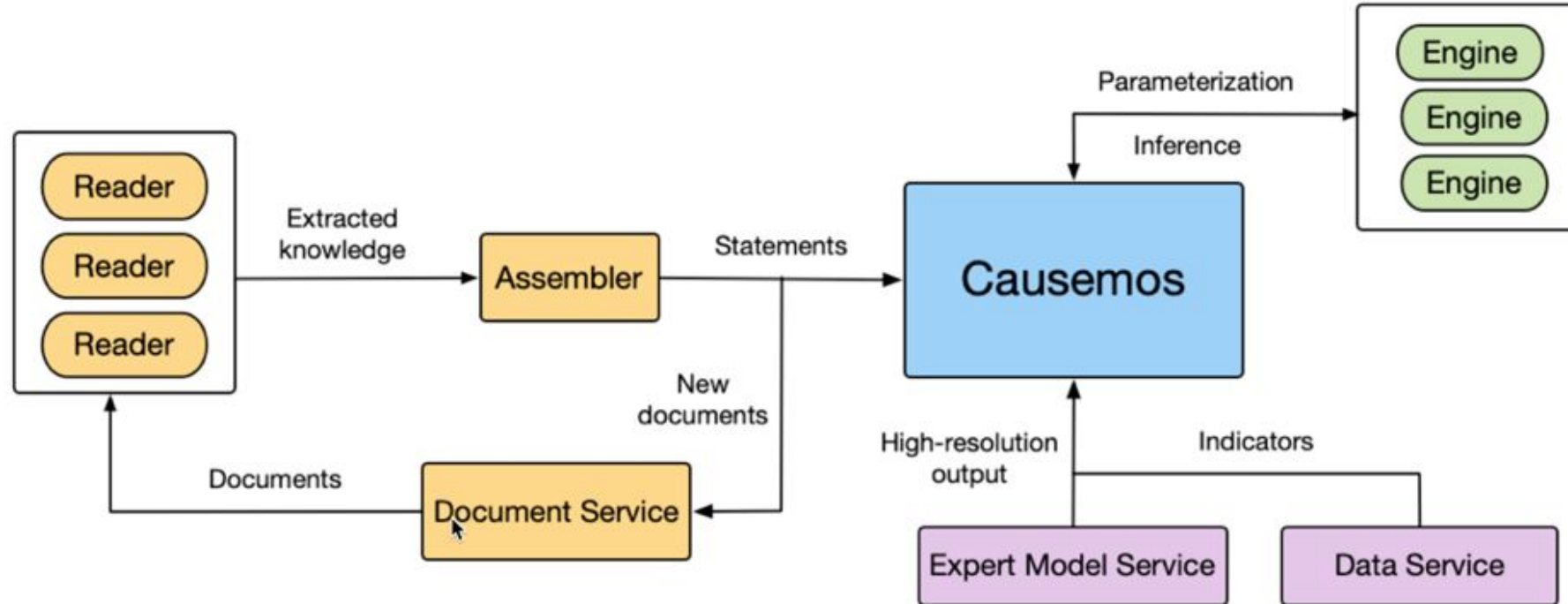
- Platform developed for the WM program.
- **Abstraction layer** that synthesizes various data, knowledge and model artifacts.
- Visual, interactive, scalable support for:
 - Exploration and curation of **knowledge** graphs to extract qualitative theories of change.
 - **Data** analysis capabilities across open-source indicators and high-resolution outputs.
 - Iterative assembly of computational/probabilistic graphical **models**.
- Utilizes principles of augmented intelligence in a human-machine interface.

Data | Knowledge | Models

- | | | |
|--|--|--|
| → Structured data (numerical data / tables) | → Source knowledge (documents) | → Library of assembled models |
| → Spatial outputs from expert high-resolution models | → Structured knowledge (ontology, knowledge graph) | → Single-model parameterization, validation, execution |
| → Data analysis and transformation capabilities | → Graph exploration and curation capabilities | → Design of experiments, intervention analysis |

- Overall **conceptual structure**, ‘tabs’ in Causemos.
- Represent three different **information streams / artifacts**.
- Sections allow for sorting external capabilities, and helps compartmentalize **integration** along section axes.
- Also helps formulate **workflow** via linkages within and between different sections.

WM Program Architecture

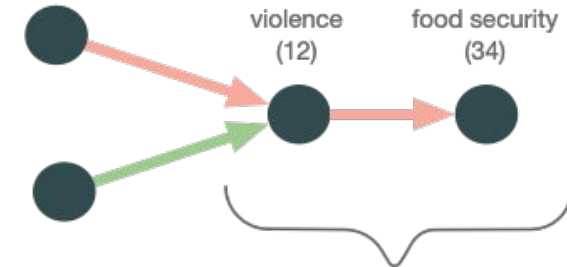


- Data
- Knowledge
- Models

Source Knowledge

The screenshot shows the causermos Knowledge Base interface. At the top, there are search filters for 'Statement Polarity is Opposite & others', 'Concept is wm/concept/causal_factor/condition/food_insecurity & 7 others', 'Grounding Score between 0.9 and 1', 'Pieces of Evidence between 2 and 5+', 'Organization is USAID', and 'Belief Score between 0.8 and 1'. Below the filters, there are tabs for 'Docs', 'Factors', 'Semts', and 'Subgraph'. A sidebar on the left shows filters for 'Location', 'Organization', 'Publication Year', 'Author', 'Category', and 'File type'. The main content area displays a grid of document thumbnails. The selected document is a PDF from FEWS NET titled 'EAST AFRICA Food Security Outlook February to September 2018'. The document content includes 'KEY MESSAGES' and a map of East Africa showing food security outcomes.

Causal Analysis Graph (CAG)



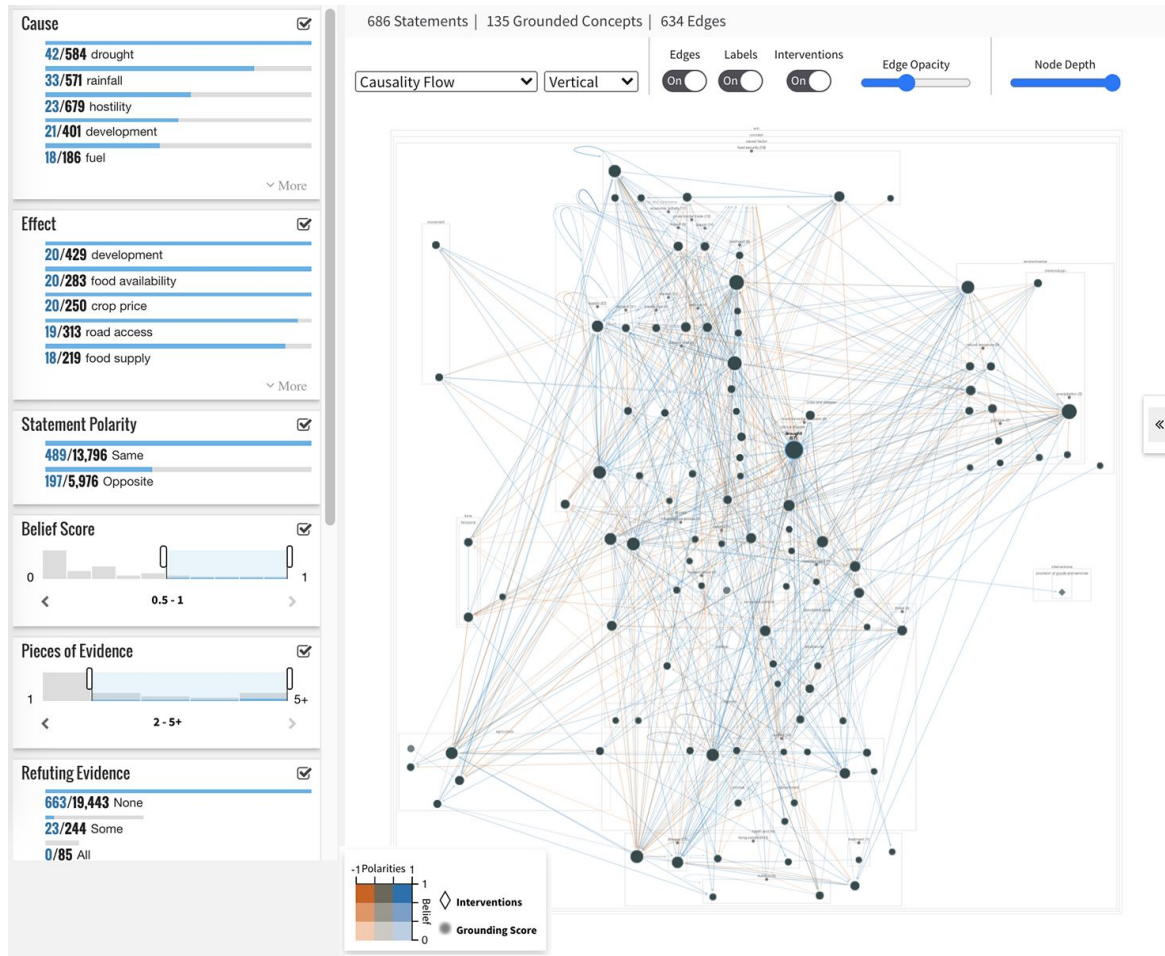
Causal Statements

Evidence Text

"The spread of conflict in the Equatorias led to a 40% national decline in food production in 2017 compared to the same February-April period in the previous year"

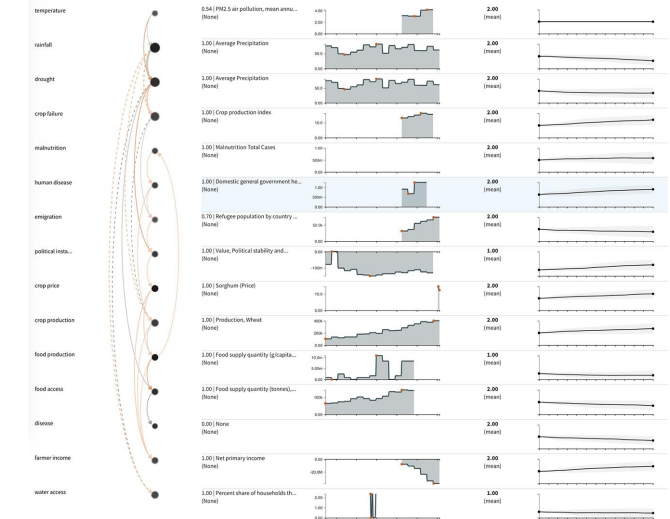
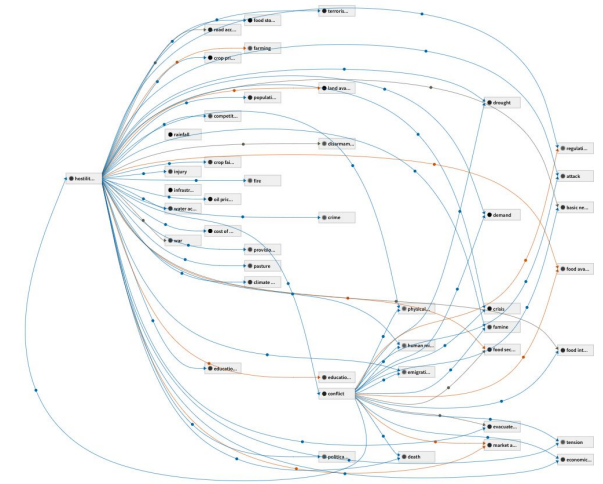
UN reports, news articles and NGO literature are examples of **source documents** (left) from which **causal statements** are extracted, which are then aggregated as a higher-level relationships between **concepts in background ontology** (right).

Causemos Views



1. A section of the full **knowledge graph** in Causemos, with attribute facets on the left and evidence drill-down on the right.

2. An extracted knowledge **subgraph of interest** represented as a flow graph.



3. A **parameterized graphical model** (arc diagram), with each concept (left) grounded in a time-series (dark grey), with the model being projected forward in time (right)

JL-YH Combined

Engine: DySE - 12 months

Run

Reset

Auto Run

Causal Flow

Conf. Band

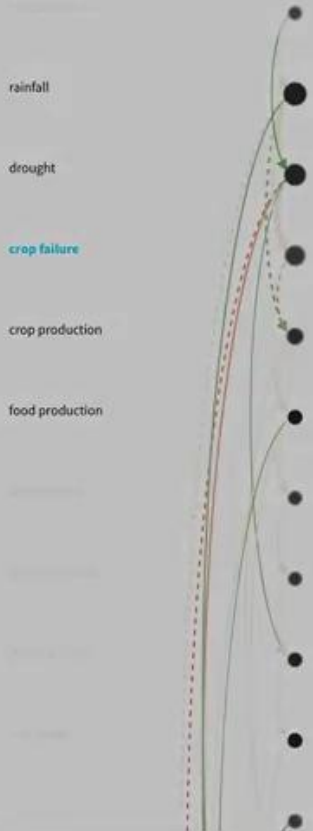
Publish

Download

Back

155 Statements | 21 Grounded Concepts | 34 Edges

Concepts



Indicator	2015 Jan	Historical	2017 Dec	Initial Value (func)	2018 Jan	Projections	2019 Jan	Final %chg
1.00 Average Temperature (None)	[Chart]	[Chart]	[Chart]	3.00 (mean)	[Chart]	[Chart]	3	--
1.00 Average Precipitation (None)	[Chart]	[Chart]	[Chart]	2.00 (mean)	[Chart]	[Chart]	1.3	-35.00 %
1.00 Average Precipitation (None)	[Chart]	[Chart]	[Chart]	2.00 (mean)	[Chart]	[Chart]	2.72	36.00 %
1.00 DSSAT (None)	[Chart]	[Chart]	[Chart]	0.00 (mean)	[Chart]	[Chart]	3.06	--
1.00 Production, Wheat (None)	[Chart]	[Chart]	[Chart]	2.00 (mean)	[Chart]	[Chart]	2.19	9.50 %
1.00 Gross Production Value (consta... (None)	[Chart]	[Chart]	[Chart]	2.00 (mean)	[Chart]	[Chart]	1.39	-30.50 %
1.00 Number of children aged 6 to 5_ (None)	[Chart]	[Chart]	[Chart]	2.00 (mean)	[Chart]	[Chart]	2.47	23.50 %
1.00 Number of deaths ages 5-14 yea_ (None)	[Chart]	[Chart]	[Chart]	3.00 (mean)	[Chart]	[Chart]	3.45	15.00 %
1.00 Value, Political stability and... (None)	[Chart]	[Chart]	[Chart]	2.00 (mean)	[Chart]	[Chart]	2.7	35.00 %
1.00 Wheat Price (None)	[Chart]	[Chart]	[Chart]	3.00 (mean)	[Chart]	[Chart]	3.55	18.33 %
1.00 Logistics performance index: (None)	[Chart]	[Chart]	[Chart]	2.00	[Chart]	[Chart]	2	

Experiments (initial/last val)

Indicators

crop failure Edit

Indicator: Decision Support System for Agrotechnology Transfer - yield

Source: DSSAT

Description: The Decision Support System for Agrotechnology Transfer (DSSAT) comprises dynamic crop growth simulation model for over 40 crops. The model simulates growth development; and yield as a function of the...
[Show More](#)

Category: Agriculture

Maintainer: Cheryl Porter, cporter@ufl.edu

Value: 5.30M kg [dm]/ha

Spatial Function: sum

Temporal Function: mean

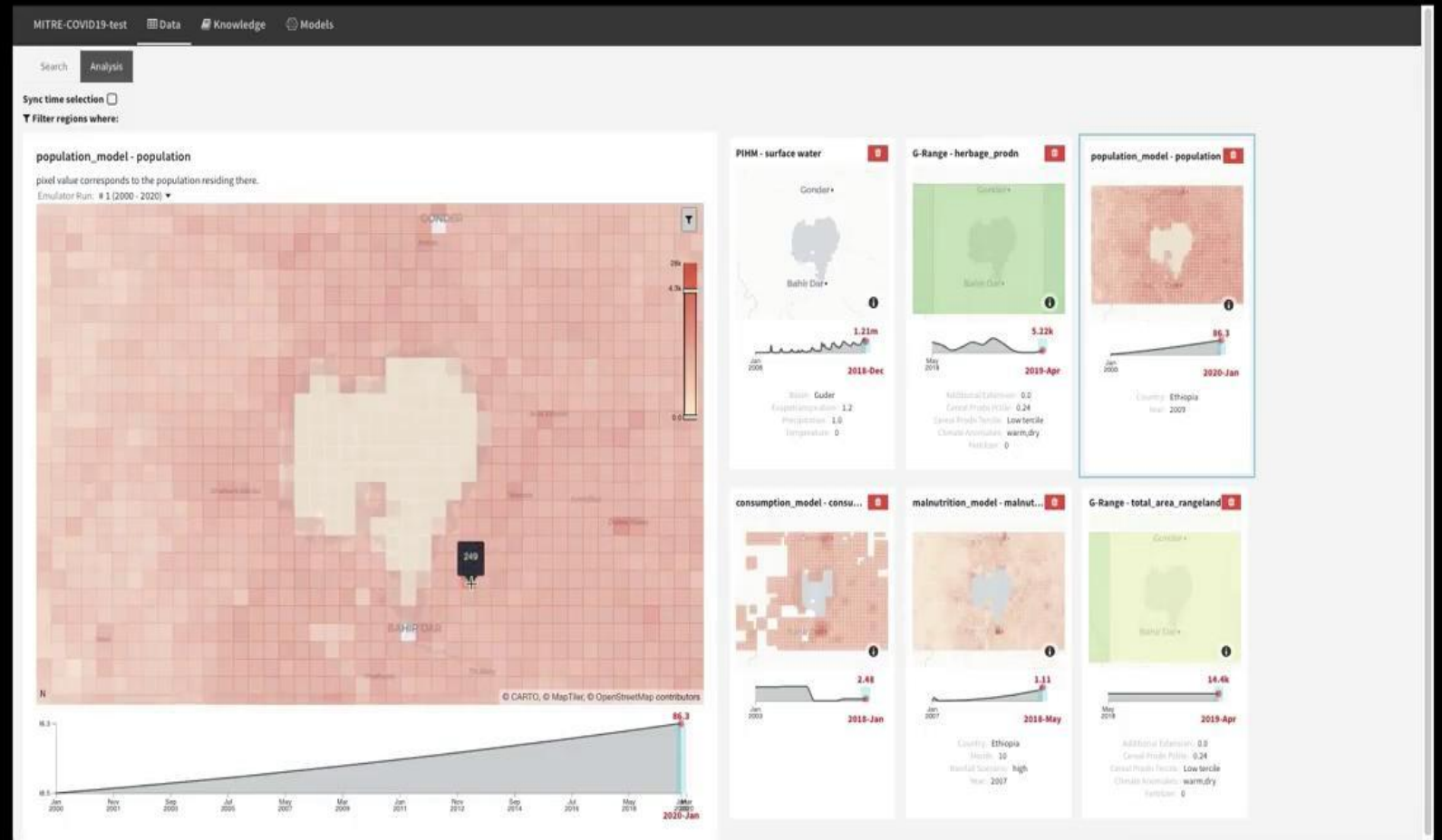
Yield in 2006: 6.05M kg [dm]/ha

Summary trend chart thumbnails allow to compare experiment results.

Data View

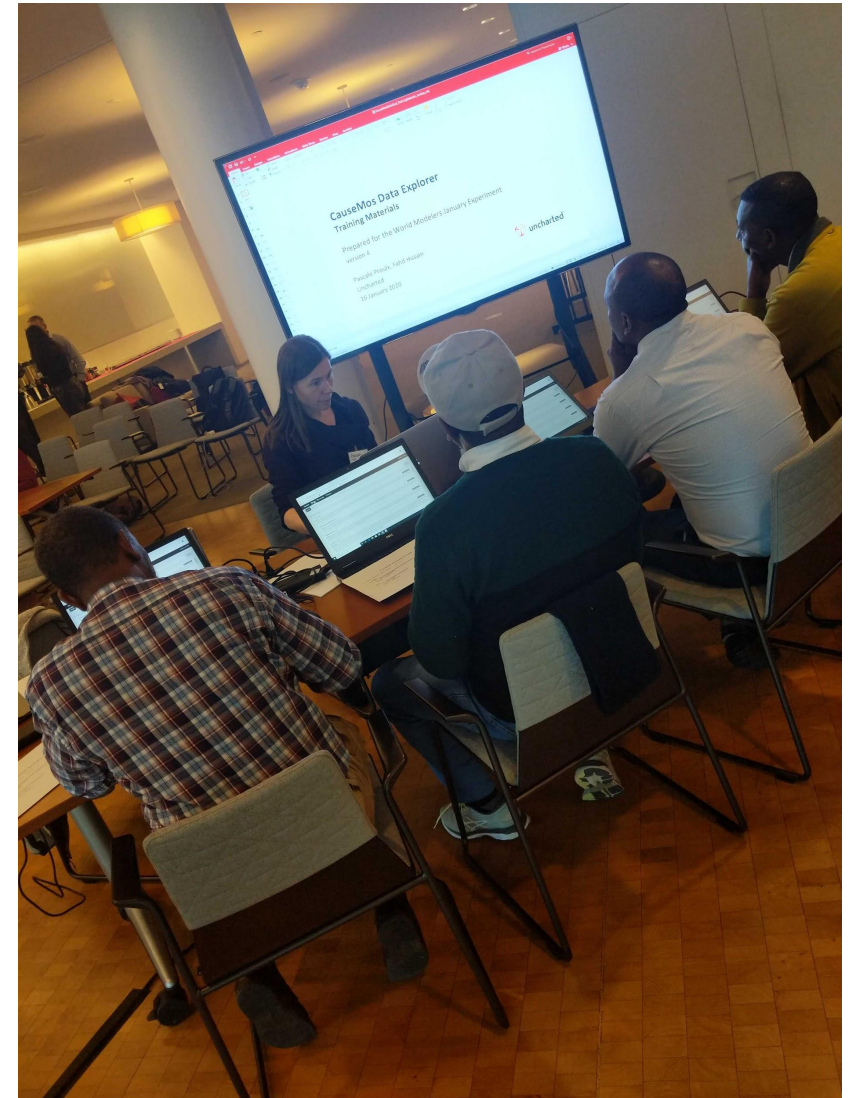
- Developed to support empirical questions of available structured or high-resolution map data.
- Analysis functionality for algebraic queries across outputs to see where conditions hold across spatial regions.
- Eventually want to use composite data to ground qualitative graphs.

see talk for video



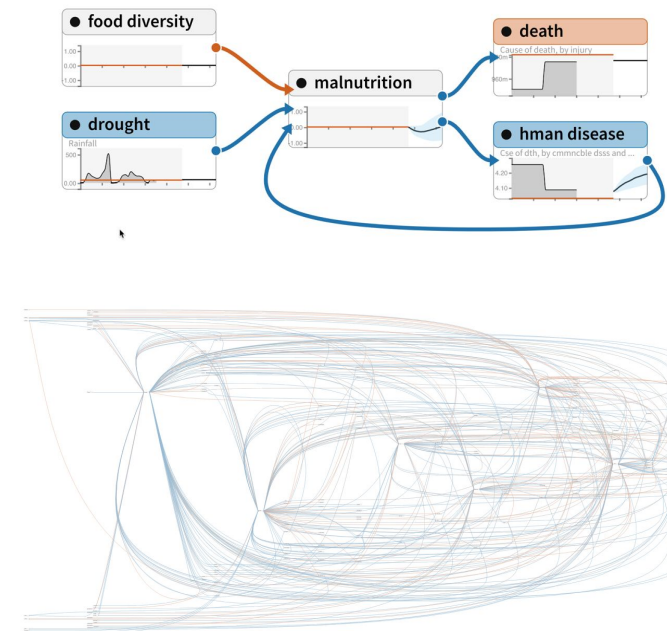
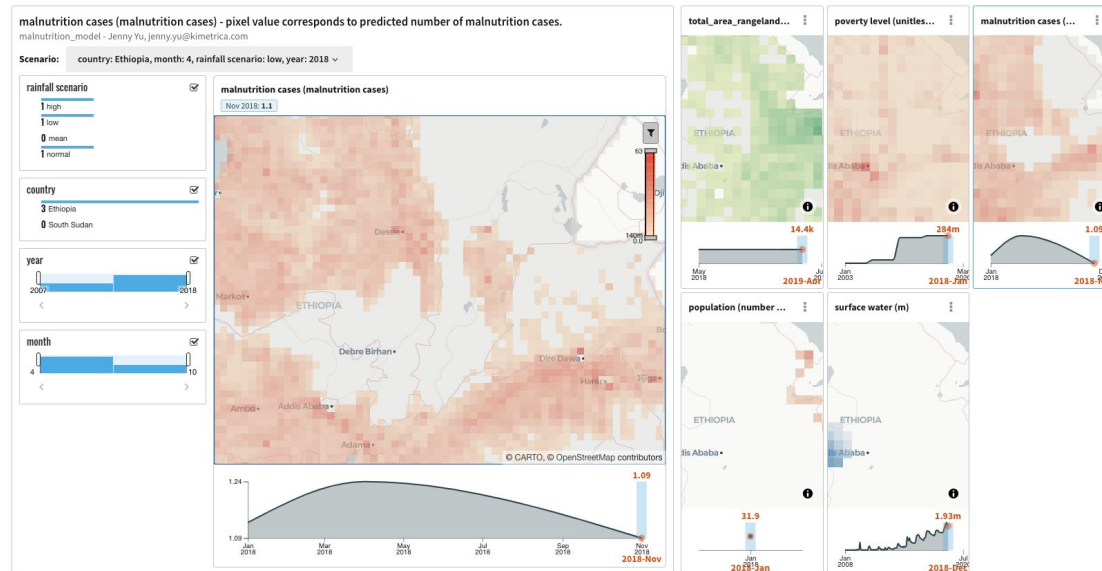
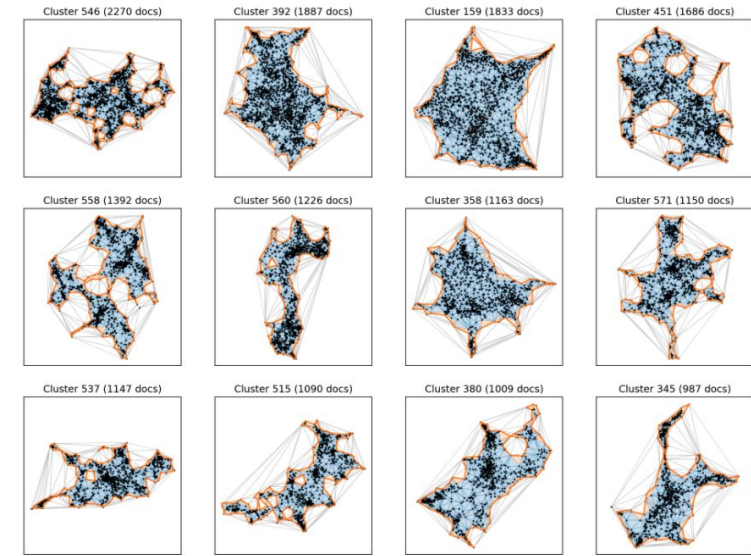
User Engagements

- Current use case around food security and linked issues in **Ethiopia**.
- Ethiopian stakeholders (academics, modelers, agricultural consultants) with support from the **Bill & Melinda Gates Foundation** and **Luma consulting**.
- Multiple successful user-focused experiments and system evaluations.




Future Causemos R&D

- Ongoing R&D to extend system to incorporate **user feedback** for next round of engagements, focusing in particular on iteration between qualitative and quantitative modeling workflows.
- Much **viz and ML** to be furthered, particularly in spatial analysis, large-scale graph visualization, model execution / validation, hierarchical clustering, mixed-initiative recommendation systems, and causal inference.



Automated Scientific Knowledge Extraction (ASKE)

Covid-19 Changed How the World Does Science, Together
Never before, scientists say, have so many of the world's researchers focused so urgently on a single topic. Nearly all other research has ground to a halt.




French lab scientists working on potentially infected patient samples at the Pasteur Institute in Paris in February. France's Mechanism Press

By Matt Aposze and David D. Kirkpatrick
Published April 1, 2020 · Updated April 14, 2020

Science Contents News Careers Journals

Read our COVID-19 research and news.

SHARE



Researchers at the Pasteur Institute in Lille, France, at work on the new coronavirus on 20 February. SYGMA LEFEBVRE/GETTY IMAGES

'A completely new culture of doing research.'
Coronavirus outbreak changes how scientists communicate

By Kai Kupferschmidt | Feb. 26, 2020, 2:05 PM

Coronavirus exposes the problems and pitfalls of modelling

Models based on assumptions in the absence of data can be over-speculative and 'open to gross over-interpretation'

- [Coronavirus - latest updates](#)
- [See all our coronavirus coverage](#)



FiveThirtyEight

Politics Sports Science Podcasts Video

APR. 4, 2020, AT 1:11 PM

Coronavirus Case Counts Are Meaningless*

*Unless you know something about testing. And even then, it gets complicated.

By [Nate Silver](#)

Filed under [Coronavirus](#)



PHOTO ILLUSTRATION BY FIVETHIRTYEIGHT / GETTY IMAGES

- Explosion of models and scientific literature.
- Model representations diverse.
- Models difficult to understand, execute, augment.
- Lack of transparency and interpretability
- Model comparison rare (structural vs parametric).
- Uncertainty compounds across modeling workflow.
- Provenance and metadata critical for understanding.
- A tense stand-off between 'model fatigue' and 'immediate action'.
- All of the above amplified at scale.

[6]

Research Approach

- **Integrated visual modeling platform** for the exploration, augmentation and analysis of extracted scientific models.
- Promote **usability, transparency, interpretability** for diverse model artifacts in terms of representation, execution, augmentation and extension.
- Go from single-model to **multi-model capabilities** for reasoning *across* different model artifacts, enabling model comparison and ensembling.
- Platform to link model representations back to **source knowledge**, enabling large-scale exploration of background knowledge for contextualization and discoverability.
- Eventually moving towards visualization of **multi-resolution or hierarchical** model structures.
- Future directions: Development of **spatial data visualizations** for hyperlocal analysis.

| Conceptual Schema

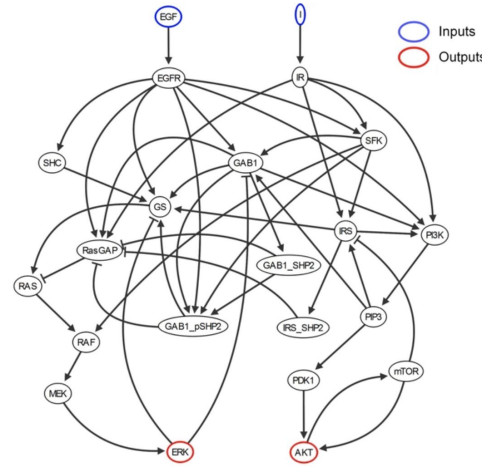
Data | Knowledge | **Models** | Experiments

- Initial focus on **models** and **knowledge**
- Articulate core **model representation(s)**
- **Contextualizing models** with background knowledge, both in terms of a structured knowledge representation (ontology / knowledge graph) and in terms of source knowledge (documents, code)
- **Model comparison**: juxtaposition, structural, parametric.
- Model execution, mutation and coupling longer-term.

Models as Graphical Models

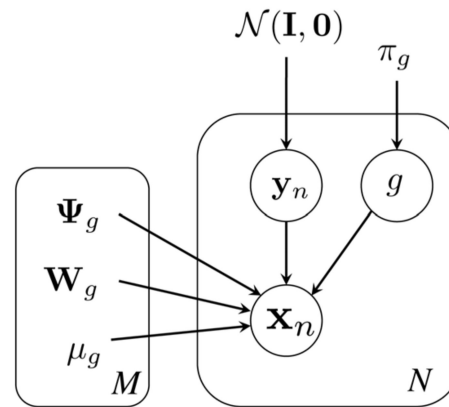
Types

- Probabilistic graphical models
- Computational graphs
- Circuit diagrams
- Biological signal networks

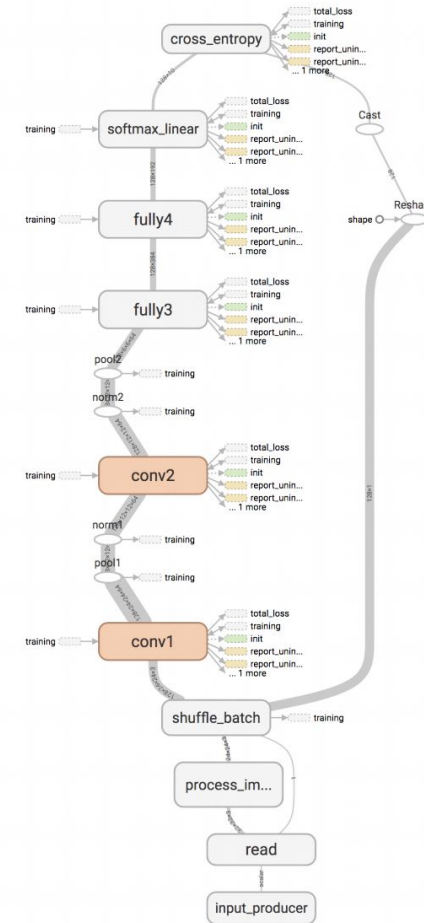


Challenges

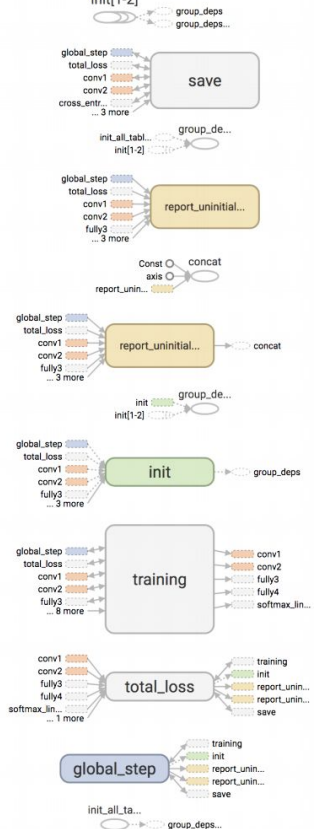
- Systems of systems of systems
- System features and metrics
- Hierarchies and complex nesting
- Various node, link and group attributes
- Heterogeneous semantics
- Nodes and links explode as system complexity grows



Main Graph



Auxiliary Nodes



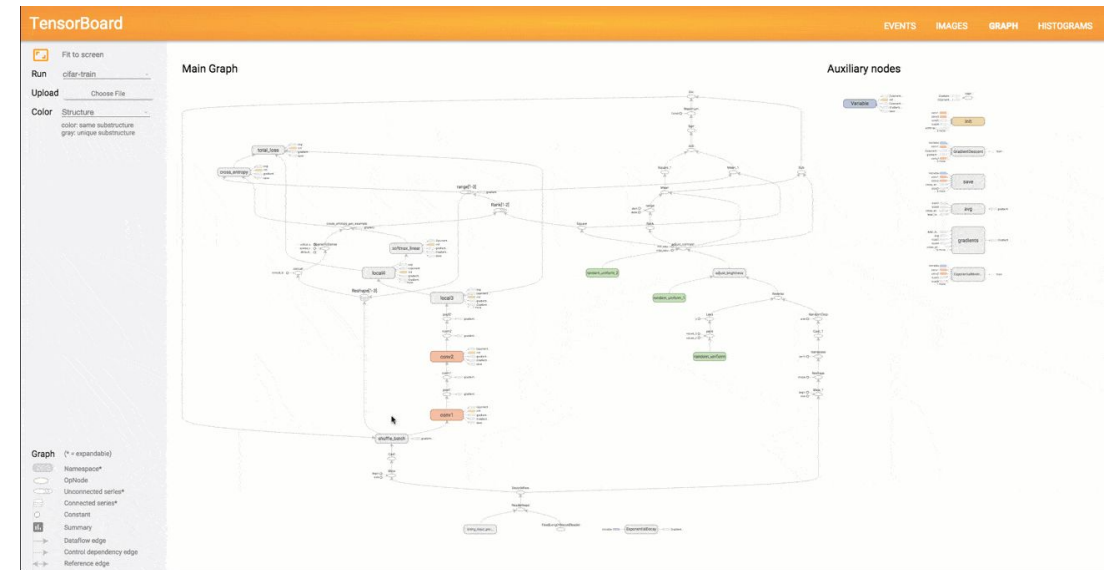
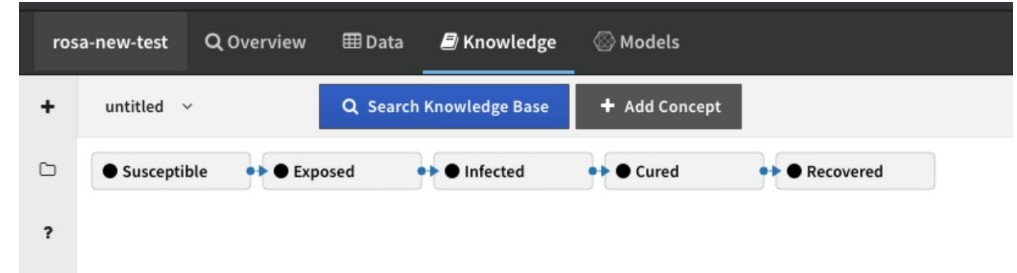
Enriched Model Representations

Start with **simple node-link representations**

- Simple attributes such as node values, link polarity, functions, global parameters (for execution).

Move to **enriched graphical representations**

- Variety of node and link attributes
- Group structures: ontological categories, decomposable routines.
- Visualization of parameter surfaces, and corresponding outcomes and rewards.
- Linked visualizations connecting different model structures and components.
- Articulation of time? Evolving graph structures?



[19]

Single Model -> Multi-Model

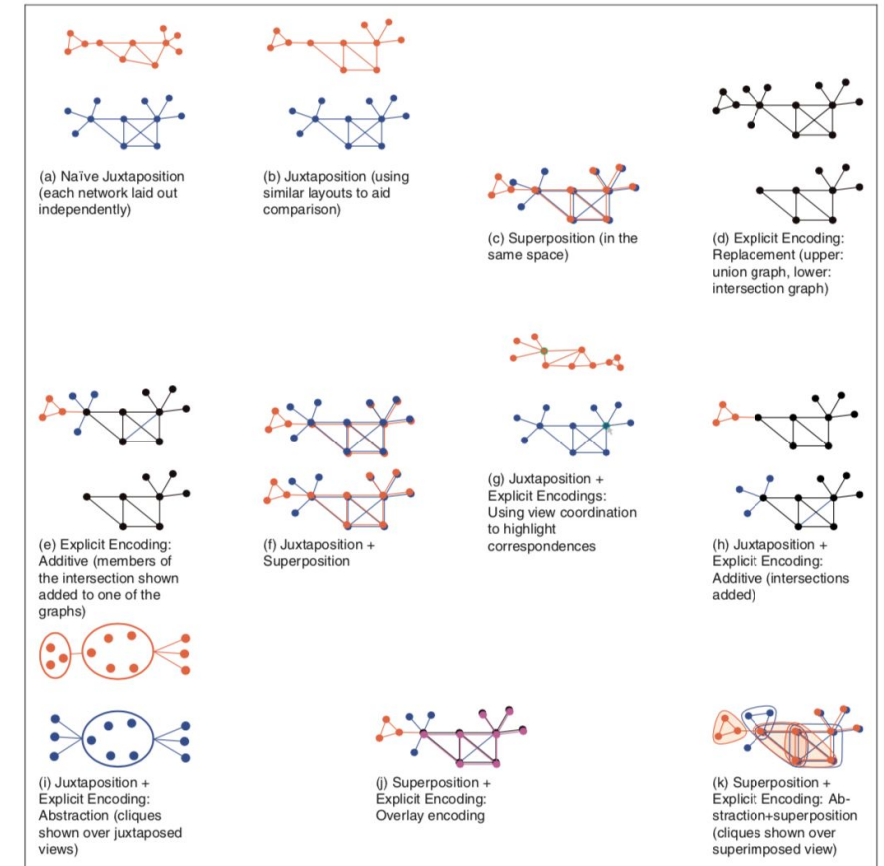
Trajectory is to move from (extracted) single model representations to a (comparative) multi-model space.

Multiple versions of a single model:

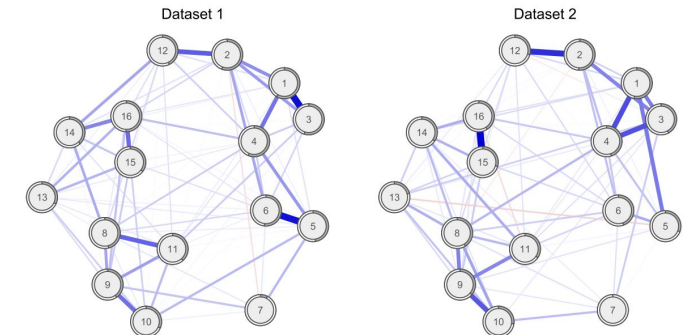
- Juxtaposition of structural alternatives, parametric variations, multiple outcomes.
- Comparison of model augmentations and extensions.

Joint analysis of multiple models:

- Identifying converging and diverging predictions across models from different families.
- Exploring joint optimization strategies across various models.
- Working with model ensembles



[9]



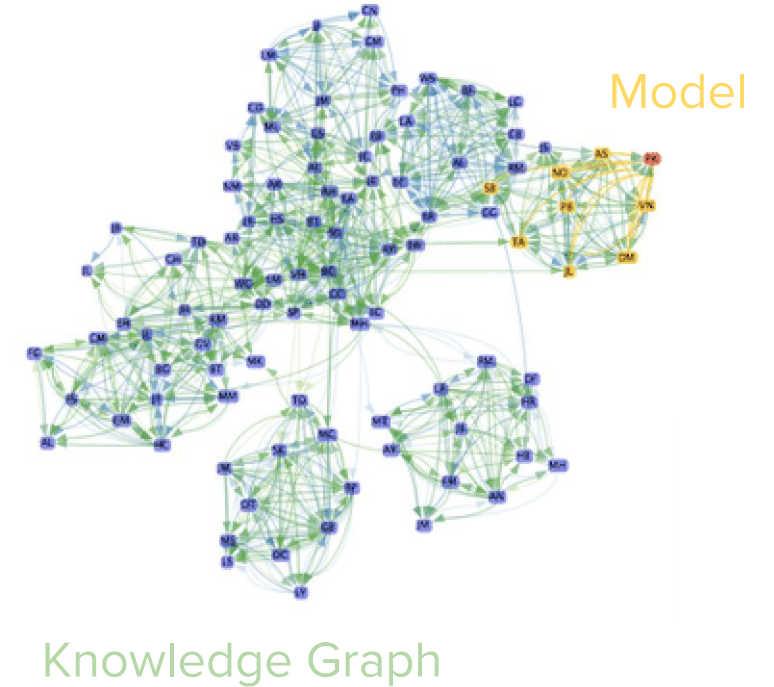
[8]

Extracted Model < > Background Knowledge

Model representations also need background knowledge representations.

These can take the form of model assumptions, model and parameter metadata, input data requirements, links back to source literature or code, juxtaposition of extracted model in larger knowledge graph...

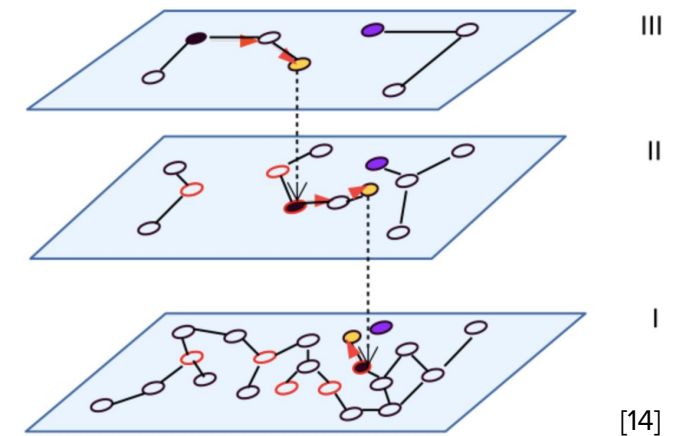
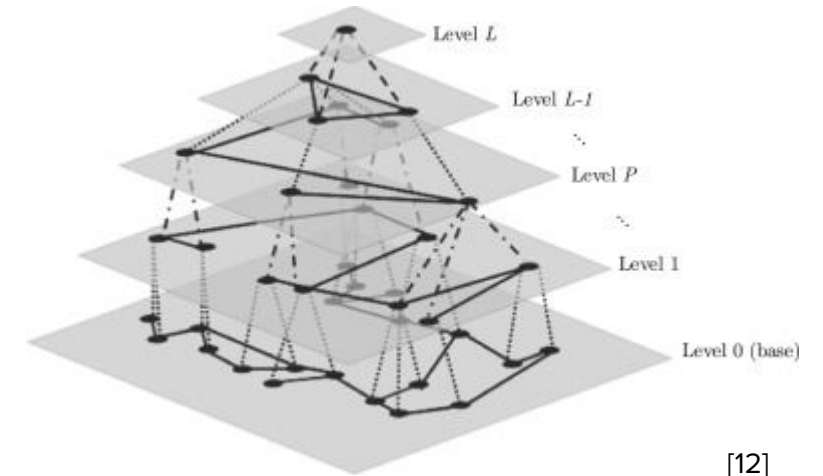
Background knowledge exploration will be important for model contextualization, augmentation and extension of existing models, as well as discoverability of related models.



[7]

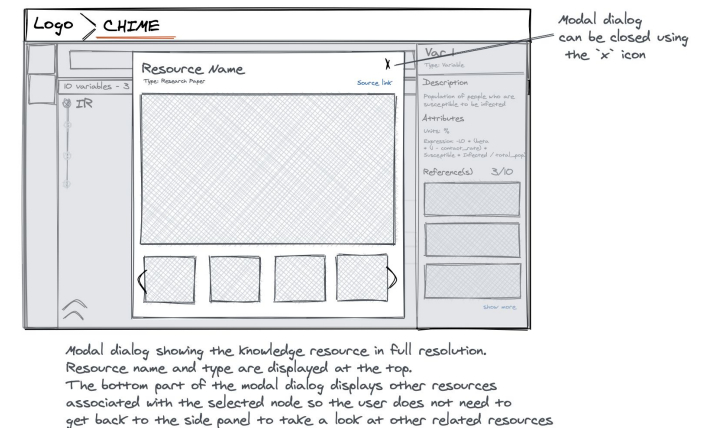
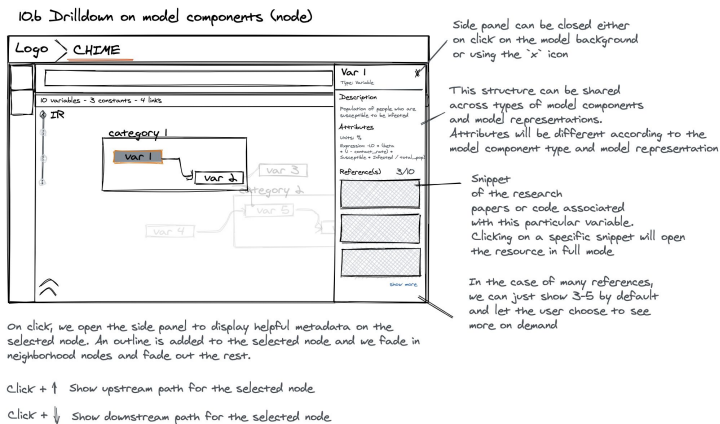
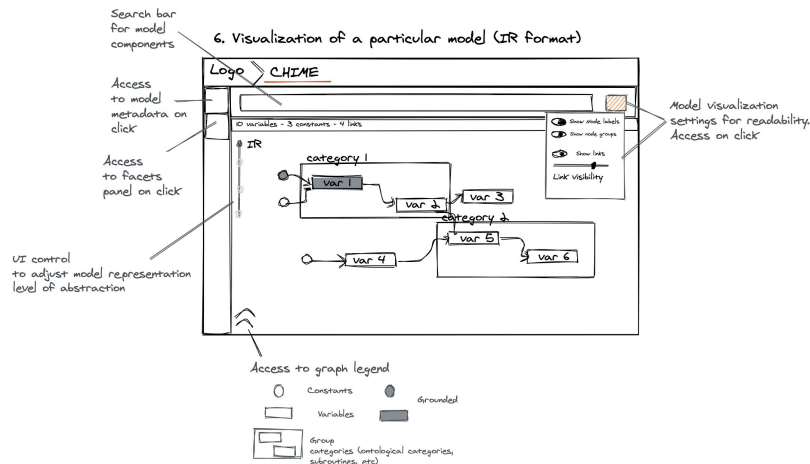
Hierarchical Models?

- Eventual vision to move towards visualizing interactive hierarchical model structures.
- **Single-model** case: model decomposable as nested sub-systems, where nodes can be unpacked to lower-level functional subgraphs or subsystems.
- **Multi-model, multi-resolution** case: stacked hierarchical layers of models from 'macro to micro' (from population-level models to biological models, for example).
- Various challenges:
 - Need full articulation of a single model as nested sub-systems, with interactions at lower levels propagating up in transparent and traceable ways.
 - Multi-model, multi-resolution case very complex, requiring a formal expression of hierarchy levels, correct placement of models at levels, establishing links between coarser and finer graph structures, articulating functional mappings (if any) between levels...

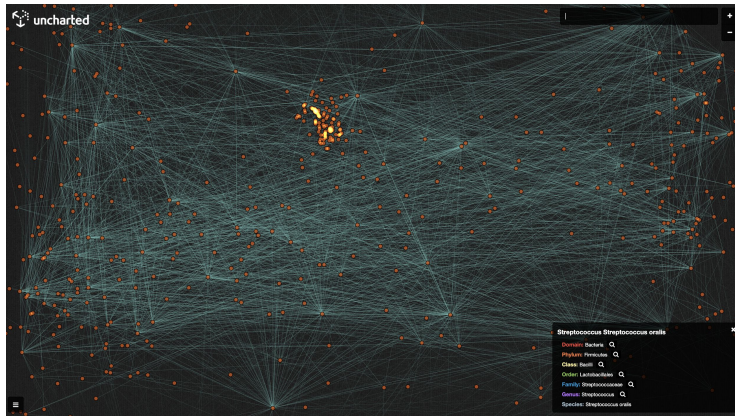
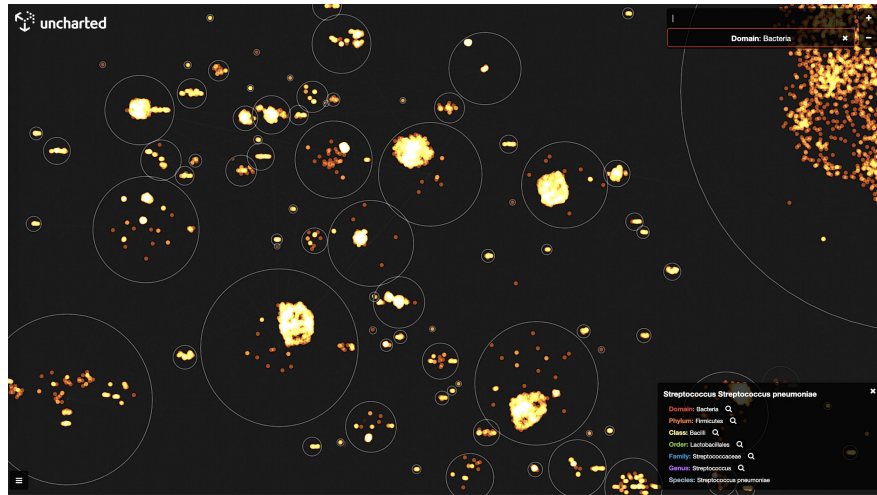


Initial Prototypes + Design

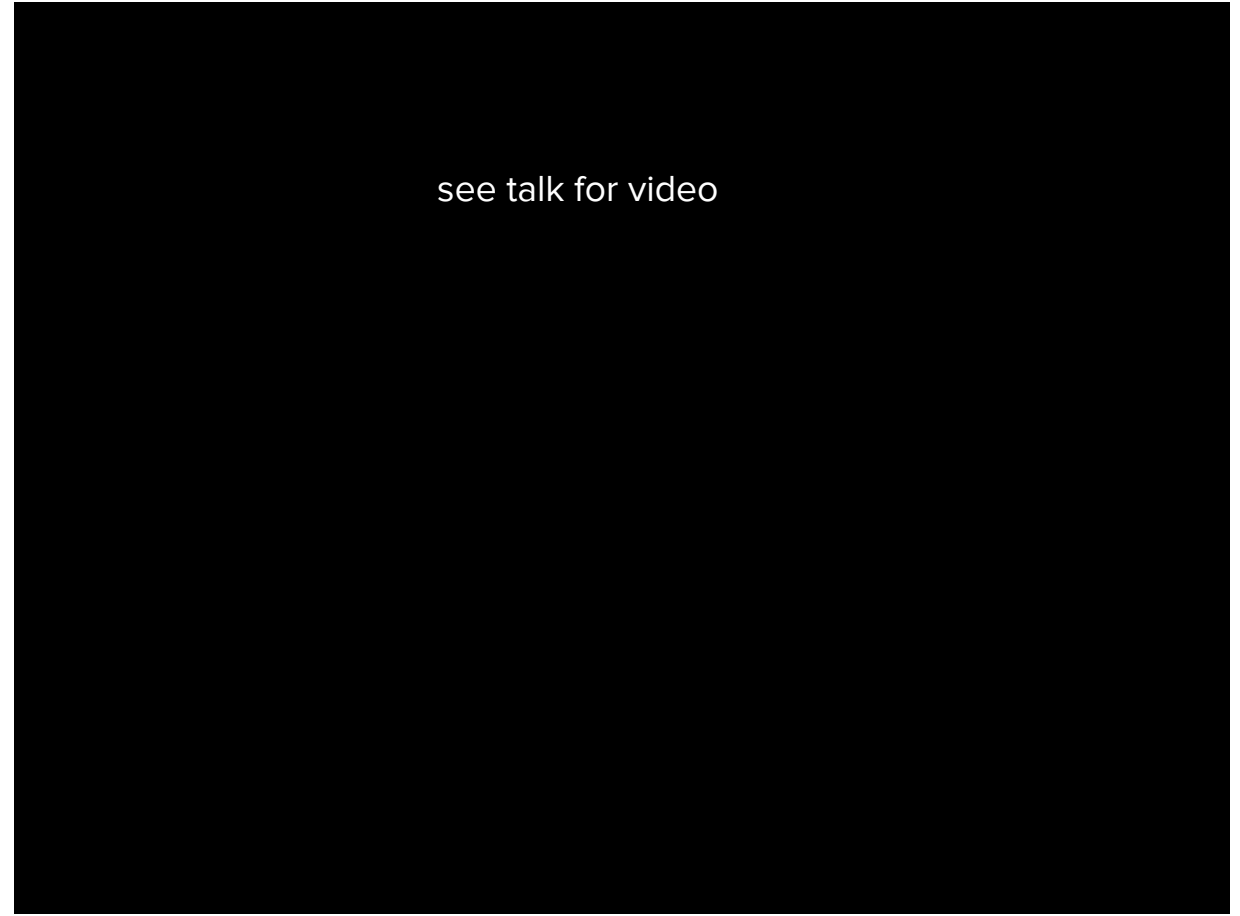
- Platform must cater to models at different levels: population-level epidemiological models and molecular-level biological models.
- Initial prototyping with different representations to understand semantics.
- Iterative exercises to build on design structures in light of potential upcoming research.
- Conceptual work to establish representation hierarchies, workflows tying together capabilities, etc.



Scalable Graph Visualization Prototypes



Genome data with 60k nodes / 60 mil edges. Hierarchical Louvain clustering used to allow interactive zoom to decompose coarse clusters into finer graphs.



Layout preserving 2D to 3D conversion and high performance rendering experiment for graph of thousands of nodes with coloured groupings.

III. Towards a Paradigm

| Challenges (1/2)

Various challenges keep reappearing in these visual modeling research efforts:

- User resistance to change. Familiarity with existing workflows leads to bias towards the contours (and limitations) of existing technologies.
- Preconceived ideas and prior knowledge carried in by users, so there must be support for the insertion of user mental models into existing knowledge. This sort of flexibility is a modeling and engineering challenge.
- Different user roles such as model builders, model tweakers, model consumers. Different levels of expertise and background knowledge, which again requires design flexibility.
- Encoding metadata (descriptions, parameter interpretations, sensible output characteristics) of models or model outputs remains mostly a manual process. Real obstacle for users looking to understand knowledge.

| Challenges (2/2)

- Even with models as graphs, common forms are hard to articulate. At the API level, node-link objects get complicated quickly with various exceptions. At the visual representation level, semantics often do not align, and interactions become inconsistent across models.
- Uncertainty compounds at each step of the workflow. Mechanisms are needed to track and trace the sources of uncertainty inherent to subjective workflows.
- Conceptual hierarchies are needed to provide aggregation for visual simplification and organization - but aggregations are often lossy, ill-fitting, lack proper coverage or granularity.
- Engineering a platform that spans complex interconnected services, with each evolving with a particular research agenda, is not trivial.

Visual Modeling: Representation

- Core representation is all models cast as graphical models of a few core types: node-link directed graphs, computational graphs, more complex flow structures like circuit / wiring diagrams.
- Core model components are nodes, edges, groups, or combinations thereof, with different types and semantics possible.
- Ongoing adjustment to maintain the abstraction sweet spot for visual representation as model types, components and functionality grows: need the right amount of generalization to span various models, but with a flexible structure that captures the critical particulars for each model.

Visual Modeling: Users & Workflows

- Visual modeling aims to enable a multi-domain, multi-model space. Modelers with expertise in a domain immediately become general modelers when immersed.
- Iterative, non-linear workflows are required, consistently moving between knowledge, models and data. Enable the user to jump between different spaces and stitch together different artifacts.
- As capabilities and ease of iteration in workflows increases, the space explored expands very quickly. Provenance of data, knowledge and modeling decisions - along with bookmarking, annotations and user management - all are needed very quickly.

Visual Modeling: ML

- User interactions full of implicit and explicit contextual clues. Machine-assisted guidance and machine-intelligence suggestion / recommendation services are essential, as are mechanisms for eliciting, capturing and incorporating user feedback.
- Interactive ML services for such a platform must be interpretable, lightweight, user-tweakable, and developed with active-learning in mind. Offline or back-end ML services can be deployed in more typical ways.
- Interpretation, transparency and debugging of models and output is critical for establishing user trust - work from current AI viz research can be leveraged here.

Visual Modeling: Linking & Abstraction

- Given the scale of the knowledge and data often involved, conceptual organization (an ontology, for e.g.) is critical for browsing knowledge and data artifacts at scale.
- Graph aggregations, hierarchical clustering, data summaries are all heavily used visual components. Principles of progressive disclosure at play.
- Frequent oscillation between background and foreground, between overview and drill-down, between high-level and granular. Linked views and linked artifacts are consistently utilized.
- Consistent, ever-present contextualization of model artifacts against knowledge, or knowledge artifacts against data, or data artifacts against models.

Visual Modeling: A Paradigm

- A platform aligned with a **paradigm of visual modeling** enables general modelers to move through various stages of a modeling workflow interactively, iteratively, visually.
- Capabilities include engaging or assembling diverse model representations from different domains; persistently have access to knowledge and data spaces for both context and separate analysis; allow for modeling and meta-modeling perspectives - *and* enable all this through the medium of visualization itself.
- **Core components** of this approach involve graphical modeling, knowledge contextualization, hierarchies/abstraction, user-in-the-loop, linked artifacts and non-linear workflows.
- Some **benefits** are speed of iteration, synthesis of information, general visual forms for broader engagement, able to engage different aspects of compositional problems.
- Thoroughly **interdisciplinary** paradigm: equal emphasis on conceptual architecture, design, user engagement, interaction, visualization, workflows, engineering *and* modeling.
- Lots of **research and synthesis** still to come to fully articulate the paradigm of visual modeling.

Thank you!

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External Partners

Atlas AI

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University of Arizona

University of Florida

University of Pittsburgh

... and more.

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