Spatiotemporal Learning in Action

Connecting Conflict Forecasting to Societal Impact Assessment with HydraNet 1.5

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PRIO VIEWS PREDICTING CONFLICT & HUMANITARIAN IMPACTS

What?

- We are concerned with **Early Warning** in order to enable **Early Action**
- For instance early **allocation of resources and personnel**
- For effective allocation, stakeholders, policymakers, and practitioners need **information beyond the expected level of furture violence** - i.e. conventional conflict prediction.
- They need **information on expected impacts**: Food insecurities, access to water, migration, health risks, gendered security issues etc.

HydraNet:

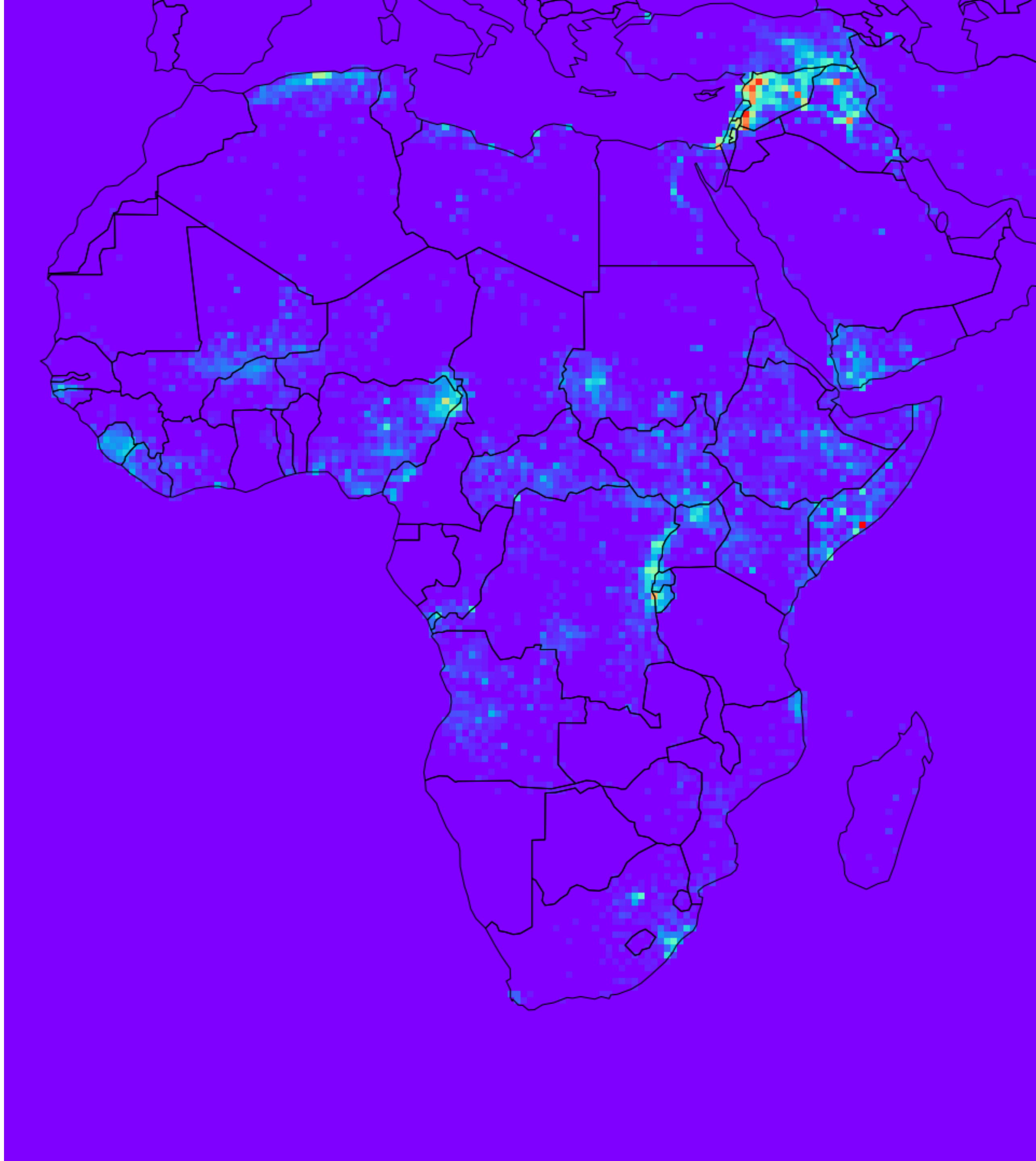
- A Deep Neural Network
- Using convolutional layers and skip connections (a U-Net)
- Structured in a recurrent manner (Long Short Term Memory)
- Capable of automatically learning and extrapolating (forecasting) spatiotemporal patterns
- For instance, useful for predicting violent conflict, or related phenomena, at a highly disaggregated temporal and spatial granularity

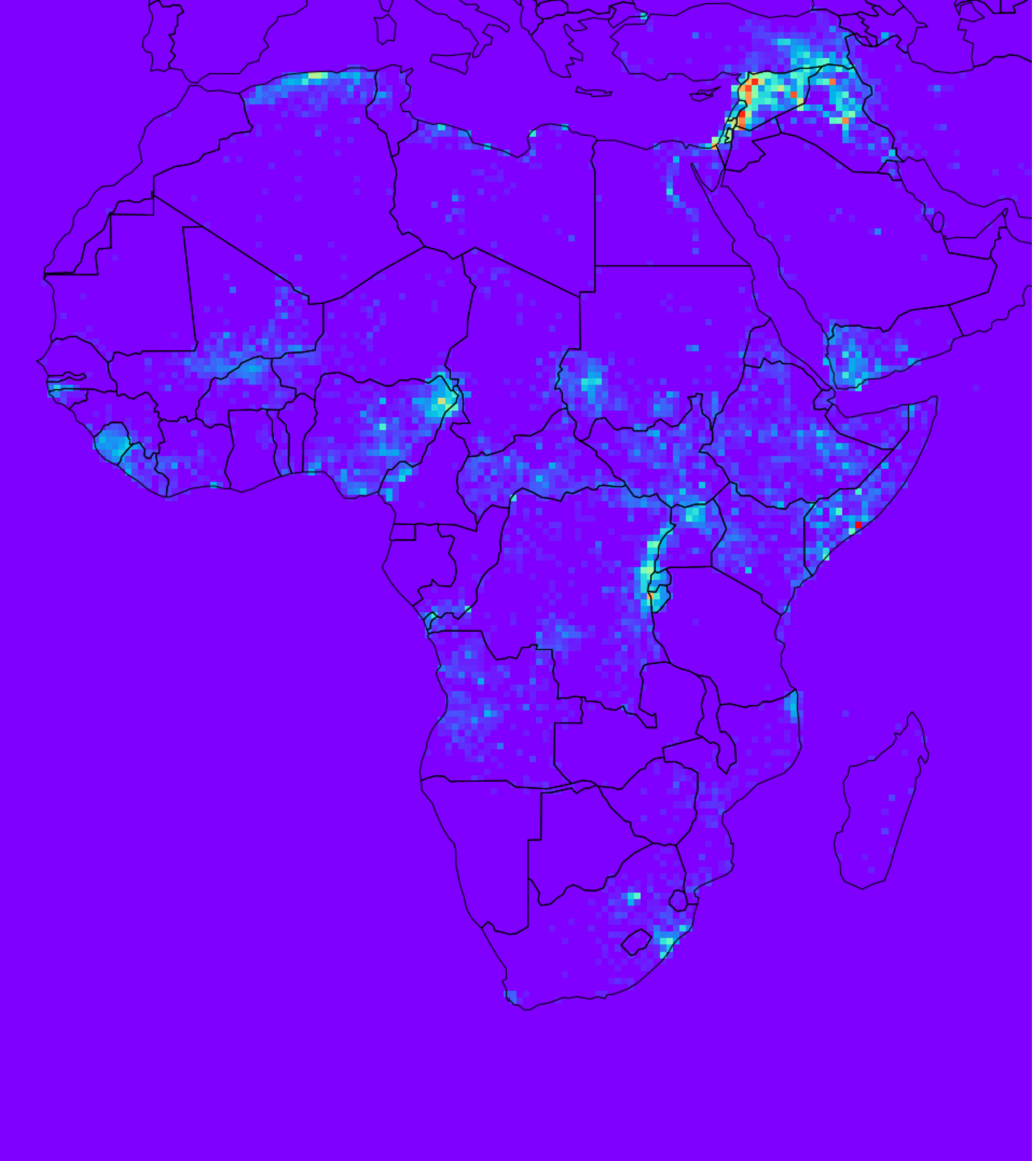
Admittable a lot of jargon and not super helpful without some background and context - so let's rewind a bit

VIEWS: The Violence and Impact Early Warning System:

- A **machine learning** system producing forecasts of violent conflict

- New updated 36-months-ahead forecast every month





- At country (global coverage) and **PRIO grid** (Africa and ME coverage) level

- The PRIO grid (pg) is a spatial grid with square grid cells of 0.5×0.5 decimal degree

- Approximately $55km \times 55km$ at the equator.

- pg level forecasts are the focus of the rest of this presentation

When I say Machine Learning (ML) I mean:

- A subset of artificial intelligence
- Through a combination of computer algorithms and statistical tools, we allow computers to learn patterns directly from our data
- I.e. we are not explicitly programming hard rules

Example:

- Creating a chess program by writing explicit code such as "if black queen at E5 ..."

- Versus allowing an ML model to look at 10.000.000 million chess games and let it figure out the best rules itself

Example:

- If you know chess, you can imagine how overwhelming the first approach would be

- And naturally, large-scale conflict is vastly more complex than chess

ML, a driving force behind:

💬 Natural language processing and machine translation

🔎 Image recognition and computer vision

🤖 Autonomous vehicles and robotics

(Image: Johan Spanner)

Examples of data source used in VIEWS:

- **UCDP**: Monthly updated geolocated event data on armed conflicts, including information on actors, locations, and intensity (Current target of our models)

- **ACLED**: Real-time geolocated event data tracking political violence and protests, including conflict events, fatalities, and involved actor

- **DEMSCORE**: A large collection of datasets covering for instance regime types, quality of government, environmental factors, migration and much more

- **WDI**: a database containing information on global development, including economic, social, and environmental indicator

We are currently relying on:

- General-purpose ML algorithms such as XGboost and LightGBM
- Powerful algorithms working on conventional row/column data frames - spreadsheets if you will
- Not inherently designed to take account of spatiotemporal patterns
- An issue since, we would expect a given observation (pg) to be influenced by what happens in adjacent cells, both through time and space

Why?

Self-reinforcing feedback loops of violence hinder conflict resolution and increase the likelihood of future conflicts.

Such as military socialization, the militarization of local authorities, increasingly influential militaries, fragmented political economies, social network disintegration, the polarization of social identities, challenges related to reintegrating veterans, firearm circulation, and inter-group grievances, destruction of infrastructure, incurred debt, disrupted trade, impeded growth, reduce state capacity, etc.

Currently deployed solution:

- The simple solution is to manually create a **lot** of transformed features
- For instance temporal and spatial lags (e.g. conflict magnitude in spatially or temporally adjacent cells)
- And decay functions measuring time since the last conflict, last peace etc.
- Note, that these features have historically been constructed to capture phenomena such as conflict traps and conflict diffusion.

However:

We do not know the underlying functional form for conflict traps or conflict diffusion – they are in essence the product of legions of different complex phenomena.

And even if we did know the approximate functional form, there is no guarantee that the predictive power of past conflict patterns arises solely from traps and diffusion.

That is:

Data on conflict patterns is the most granular and most frequently updated data used, it ends up serving as a (high variance predictive) proxy for a host of other potentially unobserved or poorly measured factors.

In other words, the data on past conflict patterns is a sponge soaked in signals from everything that happens in conflict (also why past patterns are our best predictors).

Thus, it is simply unfeasible to harness the full predictive potential of past patterns using conventional manual feature engineering.

In sum:

😓 Manual feature engineering is a major resource drain and a hassle. Predicting an increasing number of outcomes exacerbates this issue exponentially

🧐 And, no matter the resources put into manual feature engineering, we are unlikely to effectively capture the predictive patterns we are looking for

🤔 We need a framework that is specifically designed to learn spatiotemporal patterns automatically from the data

👾 HydraNet 1.0:

Is a solution to this issue. I will not get technical regarding the specificities here, but keep to a high level of intuition. The main components are:

🧠 *The deep architecture*

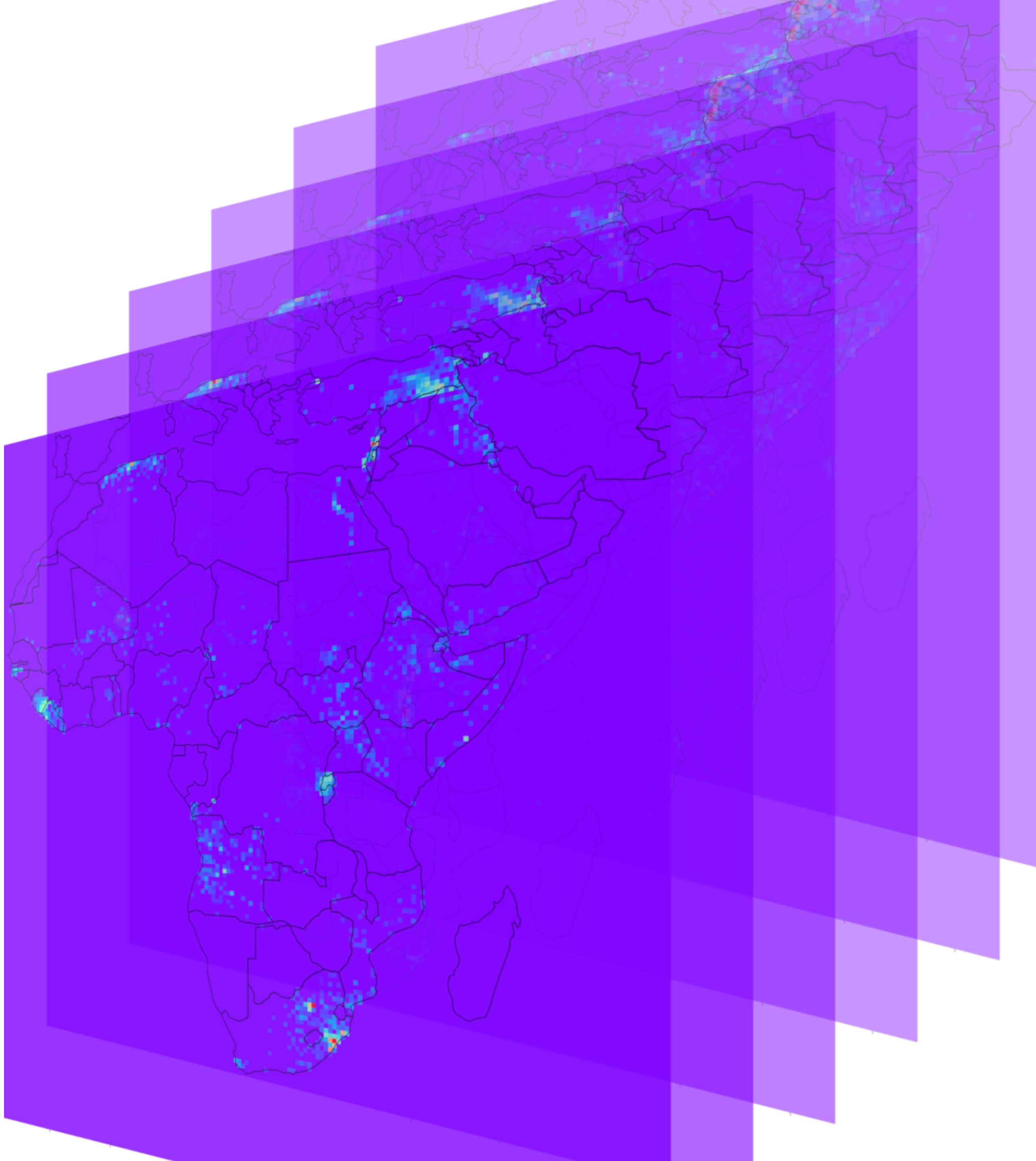
👾 *The convolutional layers*

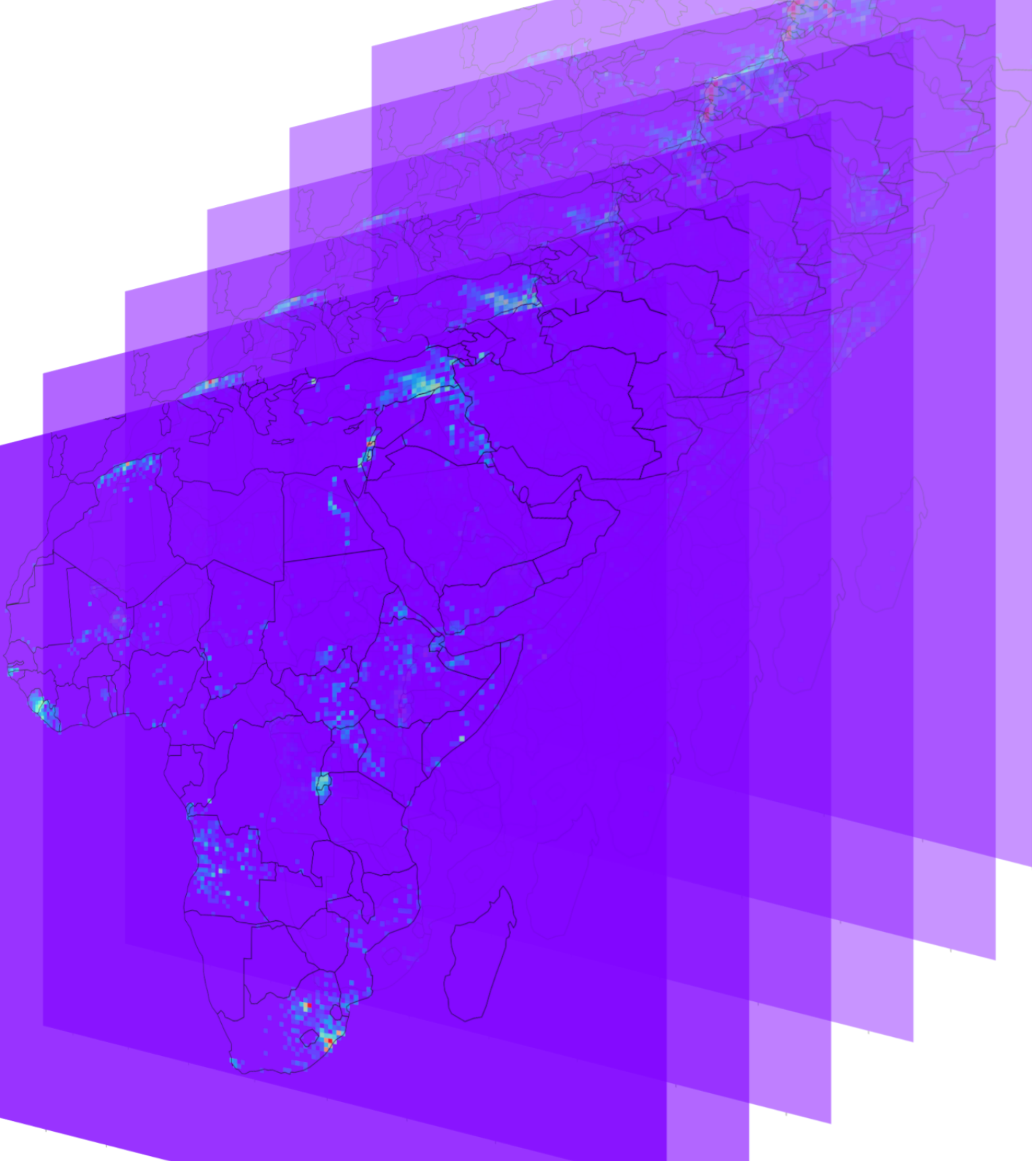
🎯 *The skip connections*

♻️ *The recurrent LSTM structure*

Analogy 1:

- Imagine predicting the next frame in a movie,
- You could consider the current frame
- The last couple of frames
- And the plot's general progression.
- Probably a manageable task

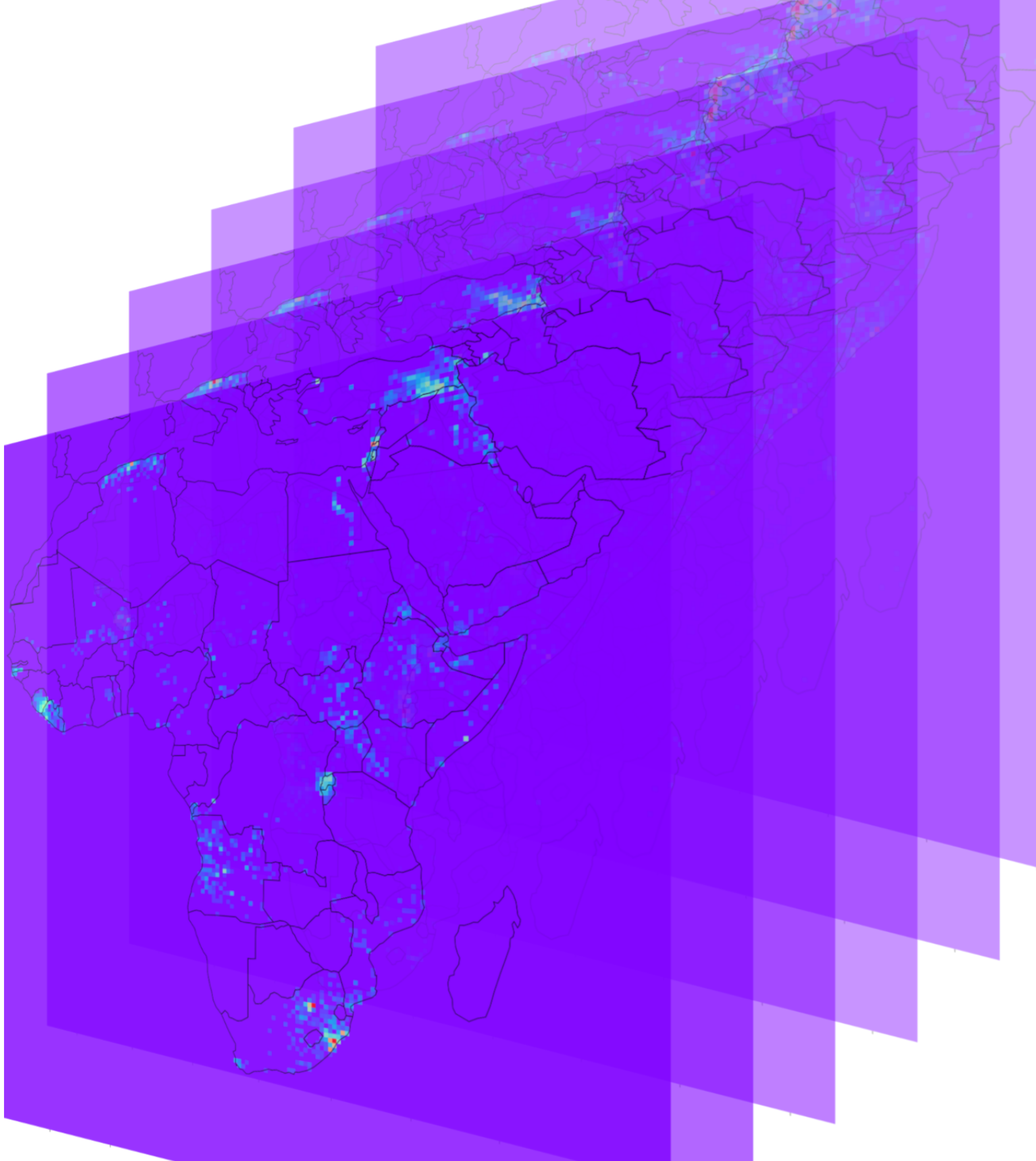




Analogy 2:

- A stack of monthly satellite images, each depicting global conflict fatalities
- The stack covers ten years
- Examine the stack from the first to the last month
- Noisy and complex yet discernable spatiotemporal patterns emerge

- Including clusters, trends, and sporadicities
- Some patterns generalize globally, while others vary by location
- Can be traced through space and time, enabling qualified predictions of "what-happens-next"
- Less accurate as we forecast further into the future, but they remain far superior to arbitrary guessing



Thus the motivation for HydraNet was to:

Develop a specialized "machine" capable of processing temporal sequences of images (grids) to learn intricate spatiotemporal patterns directly from data.

It should prioritize generalization across time and space while retaining specific historical information for each grid-cell.

The "machine" should be able to generate qualified estimates for cell-wise patterns in future, unobserved spatial grids.

HydraNet is a bespoke (custom) ML model designed specifically to excel at these tasks

Quick note:

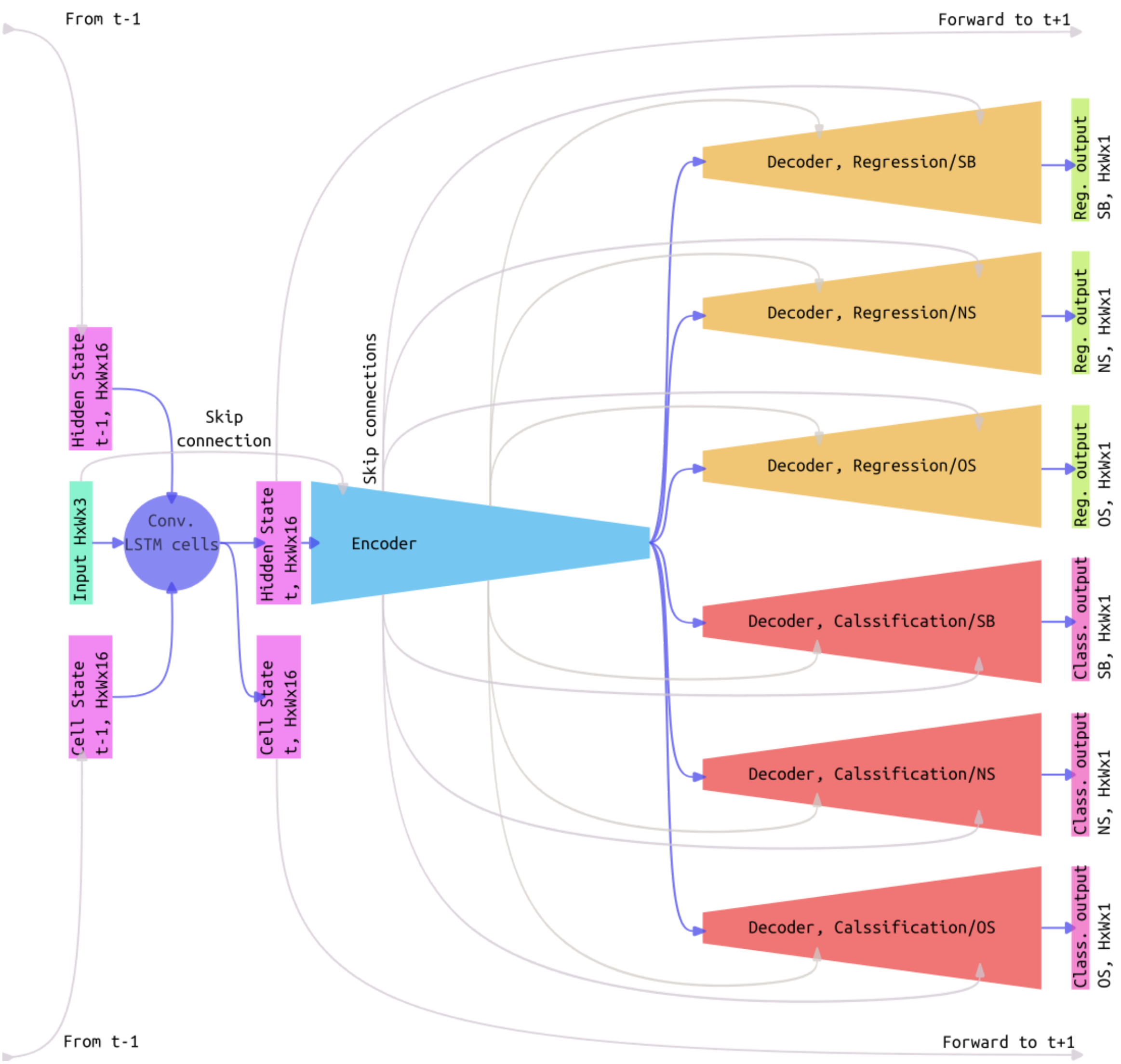
- In theory, any adequately deep neural network would be able to do this if we had infinite data and computing power.
- But only one history of violence - and only 30-ish years of data
- And compute power is always scares
- The relative strength of HydraNet is its ability to automatically and effectively learn highly complex spatiotemporal patterns given very limited data

Why "Hydra"?

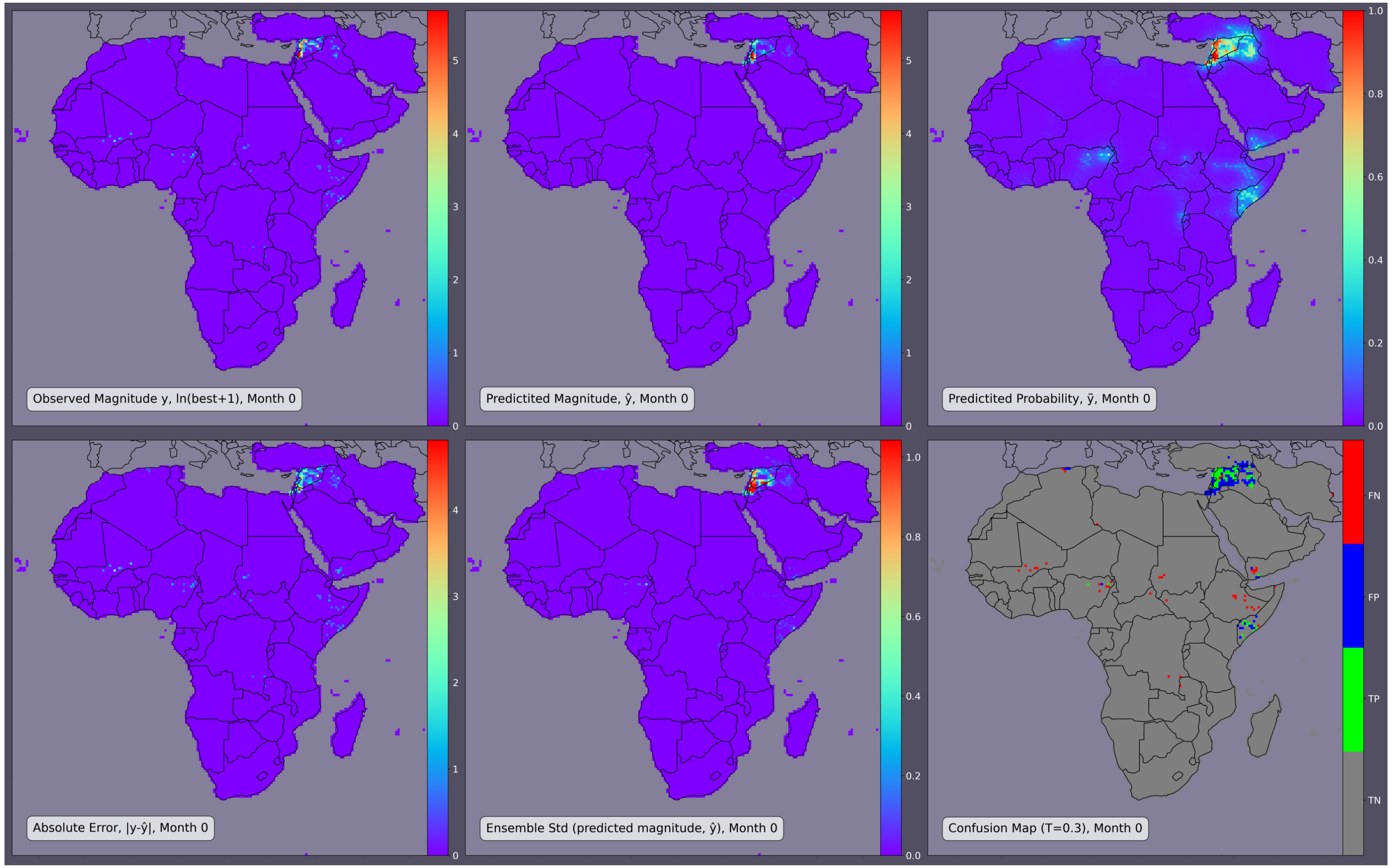
- Can forecast multiple outputs simultaneously

- Currently forecasts 3 different types of violence (**state-based**, **one-side**, **non-state-based**)

- Both probabilities (classification) and magnitudes (regression) of expected conflict fatalities



timelapse



Observed Magnitude y, ln(best+1), Month 0
Predictited Magnitude, ŷ, Month 0
Predictited Probability, ỹ, Month 0
Absolute Error, |y-ŷ|, Month 0
Ensemble Std (predicted magnitude, ŷ), Month 0
Confusion Map (T=0.3), Month 0
FN
FP
TP
TN

From 1.0 to 1.5

- Back to the fact that the point of **Early Warning** is **Early Action**
- E.g. Early allocation of resources and personnel
- For effective allocation, stakeholders, policymakers, and practitioners need more information than "simply" the kind and magnitude of expected violence
- They need information on the expected impact: Food insecurities, access to water, migration, health risks, gendered security issues etc.

To what extent can HydraNet help?

- Again: HydraNet's strength comes from its capacity to effectively and automatically learn salient and highly complex spatiotemporal patterns.

- If a phenomenon can be expected to exhibit temporal and spatial dependencies - i.e. if distances matter - then HydraNet is a reasonable candidate.

- Several of the conflict-induced impacts we are interested in can indeed be expected to exhibit some amount of spatiotemporal dependencies.

To the extent that we can muster the computational power, HydraNet can forecast an arbitrary number of spatiotemporal phenomena

However, there is probably no need to forecast everything at once…

Dedicated solutions can easily be implemented for specific rosters of phenomena of interest

Hopefully, HydraNet - or at least the ideas and components behind it - can find use outside the VIEWS consortium

Questions?

Thanks for listening!

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