Evaluating Lost Person Behavior Models

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Abstract:

U.S wilderness search and rescue consumes thousands of man-hours and millions of dollars annually. Timeliness is critical: the probability of success decreases substantially after 24 hours. Although over 90% of searches are quickly resolved by standard "reflex" tasks, the rest require and reward intensive planning. Planning begins with a probability map showing where the lost person is likely to be found. The MapScore project described here provides a way to evaluate probability maps using actual historical searches.

In this work we generated probability maps based on the statistical Euclidean distance tables from ISRID data (Koester, 2008), and compared them to Doke's (2012) watershed model. Watershed boundaries follow high terrain and may better reflect actual barriers to travel. We also created a third model using the joint distribution using Euclidean and watershed features. On a metric where random maps score 0 and perfect maps score 1, the ISRID Distance Ring model scored 0.78 (95%CI: 0.74-0.82, on 376 cases). The simple Watershed model by itself was clearly inferior at 0.61, but the Combined model was slightly better at .81 (95%CI: 0.77-0.84).

1. INTRODUCTION

Searching can be arduous, time consuming, and expensive. These characteristics justify “taking the search out” of search and rescue (SAR), a worthy but unreachable goal: some search always remains, and search requires planning. The probability of survival in land search decreases with time (Pfau 2011). Good planning makes search more efficient, reducing costs and saving lives. The first step in good planning is deciding where to search: some areas are more likely than others. In fact, some areas are so much more likely that >90% of searches resolve within a few hours based on “reflex” tasks to the high-probability areas (Koester 2008). However, the remaining cases require and reward explicit planning using methods first developed in WWII (Koopman 1980). Planning begins with a probability map showing where the lost person is likely to be, allocates search effort to minimize expected time to find, and updates the map after each operational period to account for completed searches, clues found, and possible subject motion. In wilderness search (WiSAR) this is often either intuitive or manual, but with increasing use of Geographic Information Systems (GIS) planning tools, WiSAR can create and update detailed probability maps (Doherty et al. 2014). But how to tell a good map from a poor one?

In this paper we generate and compare several probability maps for hundreds of historical WiSAR incidents for which we have good initial and final coordinates. The incidents come from the International Search and Rescue Incident Database (Koester 2010). Maps are scored using a simple and robust metric from crime-mapping (Rossmo 1999). While there are a few papers on producing WiSAR probability maps (see for example: Castle 1998; Soylemez and Usul 2006; Sarow 2011; Lin and Goodrich 2010; Ferguson 2013; Doherty et al. 2014) there has been no evaluation of the relative accuracy of different methods. This paper is the first, establishing a performance baseline we hope will be surpassed repeatedly.

In practice, the most common way to assign probabilities to search regions is with subjective estimates based on quartile distance statistics, particularly the summary statistics found in Koester (2008): a simple ‘bulls-eye’ formed by the 25%, 50%, 75%, and 95% probability circles. Thus the distance ring model serves as a baseline. We compare it to a relatively recent watershed model (Doke 2012; Doherty et al. 2014), and a novel combination of the two.

The Introduction briefly reviews WiSAR costs and the use of probability maps in WiSAR. Section 1: Scoring introduces the MapScore website, Rossmo's metric, and its desirable properties. Section 2: Data & Methods introduces the models. Section 3: Results, evaluates these models. Section 4: Discussion provides a brief conclusion and recommendation for future work.

1.1 Cost &Time

In the United States, the National Park Services (NPS) alone conducts thousands of search and rescue operations annually. According to NPS & USPP (2012), the NPS conducted 4,080 SAR operations at a total cost of $5.3 million, or roughly $1,375 per mission. Figure 1. shows the increasing costs for SAR operations over the past several years (1995-2012).

Insert Figure 1 here: Annual SAR Cost

The price appears to be rising faster than inflation: from 1992 to 2007 the NPS responded to 65,439 incidents at an average cost of $895 per operation (Heggie and Amundson 2009). However, from 2000 to 2012 the NPS responded to 53,351 incidents at an average cost of $1,163. In constant 2013 US dollars, the average increase is about $160 per case. Nearly half the total costs were overtime; the rest was mostly aircraft (Heggie and Amundson 2009). Yosemite National Park alone accounted for 25% of the total costs ($1.2 million).

Time is the other key issue. Figure 2. shows the decreasing chances of successful rescue over time for Hikers and 4-6 year-old children. (Koester 2008; Pfau 2011) The decline is due to a combination of injuries, exposure, exhaustion, and dehydration. The larger the search area, the longer it takes to search. Therefore, limiting the search area substantially improves the chance of rescue.

Insert Figure 2 Here: Probability of Success Graph

1.2 Probability Maps

Mathematical search theory (Koopman 1980) takes a probabilistic approach because, by definition, the location of any search object is unknown. Some of the earliest documented searches divided the search region into smaller cells, and assigned probabilities to each of those cells based on a structured mix of subjective and objective information. For example, Figure 3. shows maps from the 1967 search for the USS Scorpion (Henry R. Richardson and Lawrence D. Stone 2006) and the 2009 Search for Air France Flight 447 (BEA 2012). Both have been recounted in (McGrayne 2012).

Insert Figure 3 Here: Scorpion and Airplane

Search theory has advanced considerably since its origins in World War II, and modern maritime search planners like SAROPS (Kratzke, Stone, and Frost 2010) incorporate sophisticated motion models and path planning for searchers. There is nothing comparable for WiSAR. WiSAR has been slow to adopt search theory, in part because good probability maps have been unavailable, and because probability of detection varies dramatically with small-scale changes in terrain and vegetation. (There are also institutional reasons, such as the lack of central authority or central funding for WiSAR.)

Maritime probability maps are conceptually simple: there is a physics of ocean drift, however complicated. There is no equivalent for lost person behavior. Nevertheless, early work by Syrotuck (1976/2000) showed that lost persons generally stayed very close to the initial planning point (IPP): 60% were found within two miles (straight-line or crow's-flight distance). Based on his 242 cases from New York and Washington states, Syrotuck formulated a "ring" model, by noting the 25%, 50%, 75%, and 95% zones for eight subject categories including: Hunters, Hikers, Elderly, and Child.[1] Subsequent studies over the last 37 years have collected more data from various regions in the US and abroad. Recently, Koester (2008; 2010) created a unified database containing thousands of cases from around the world. For each of his categories he reported summary statistics for: crow's-flight distance, track offset, dispersion angle, find location, scenario, mobility, and survivability.

Both Syrotuck and Koester create simple probability maps (like the distance-ring model) directly from the summary statistics. In effect, this assumes that by the time the search has started, the subject is not moving appreciably. The surprisingly small distances traveled suggest this is a pretty good assumption in many cases. Nevertheless, ideally the models would account for motion during the search. Several models have been formulated (Castle 1998 and Lin & Goodrich 2010),that treat the subject's movement as a stochastic process governed by transition matrices which include, for example, a subject's preference for uphill/level/downhill, or moving from one kind of trail/vegetation to another, or simply going straight versus turning.

These approaches generate a probability map by dropping thousands of simulated subjects on the map around the IPP, and running a large Monte Carlo simulation. The advantage of this approach is that the map evolves with time. The disadvantage is that it is hard to fit the extra parameters because, almost by definition,

[1] Syrotuck's model was actually a bit more involved, and his "rings" often better resembled paper clips, but most people just used the linear distance.

we do not have any information on the lost person's actual trajectory. Progress will depend on having a good method for scoring probability maps, so the fitting algorithms can improve.

In this paper, we measure the performance of the baseline Euclidean distance model, and a recent "watershed distance" model (Doke 2012; Doherty et al. 2014) that counts the number of watersheds crossed by the lost person. Both Euclidean and watershed distance models do well because most lost persons do not travel very far.

2. SCORING

2.1 Genesis of MapScore

Rather than just scoring the cases offline, we decided to provide a public website with a live leaderboard and the potential to inspire friendly competition among potentially very different approaches. The project began after discussion with the Brigham Young (BYU) WiSAR team about how to compare their Bayesian motion model for lost person behavior (Lin and Goodrich 2010) with our multivariate models. How did either compare to the simple models implied by summary statistics? The BYU team helped fund initial work on what is now the MapScore website (Twardy et al. 2012; Twardy 2012)[2], and this paper reports baseline scores for a Euclidean distance-ring model and a simple cost distance model. The chosen score is based on the probability density assigned to the find region.

Search theory informs us that we minimize expected search time by allocating resources to maximize the "probable success rate", or the amount of probability that we "sweep up" with every unit of time (Stone 2007; Koopman 1980; Frost, John R. 1996). In theory, we might want to score a map based on expected time to find the subject given optimal plans made on the basis of the probability map and a map of detection indices for each resource. However, that would require contentious assumptions about the resources at hand, how they can be used, and their largely unknown detection indices. For purposes of portably comparing

[2] http://mapscore.sarbayes.org

probability maps, we can assume a single resource with detection equal in all regions. Then allocating resources according to the probability density or *Pden* is optimal, and we can use a metric based only on *Pden*. *Pden* is defined as the probability per unit area. The distinction between *Pden* and *POA* (probability of area) matters because many methods assign probabilities to regions of varying size. For example, the distance ring model assigns 25% probability both to the small region around the IPP and to the entire search region beyond the 75% ring. We would prioritize the former because the *Pden* is much higher. But if the final scored map has been rasterized into equal-sized pixels with values equal to the probability contained in that area, then POA and *Pden* are the same. We use a metric suitable for such a rasterized probability map.

2.2 Scoring Metric

Rossmo (1999) developed a robust metric *R,* used to compare probability maps for crime forecasting. The metric is rank-ordered, and a good model will assign higher values to the actual find location, compared to other areas. It measures the proportion of pixels that are assigned higher values than the actual find location. The absolute value depends on the image size, so MapScore uses a fixed size and scale. For each case, we place the IPP at the exact center of a 5001 x 5001 pixel map, where each pixel is 5m x 5m wide. At this resolution, models can use features as small as 10m without aliasing effects. At this size, the map extends 12.5 km in each cardinal direction from the IPP, which on average includes at least 95% of the search cases. Models assign pixels a brightness value corresponding to the estimated probability density at that pixel. (Most models will be much coarser than individual pixels, so they will divide the total probability in a region by the number of pixels in that region.)

Let p equal to the probability assigned to the actual find location, N be the total number of pixels in the image, n the number with probability greater than p, and let m be the number of pixels with probability equal to p. Then we define:

$$r = \frac{n + m/2}{N}$$

The value of *r is* then rescaled, so that the worst possible score is -1, and the best is +1:

$$R = \frac{.5 - r}{.5}$$

Because we corrected for pixels whose probability is equal to *p*, uniform (i.e. blank) maps get a score of zero, and random maps get an expected score of zero. [3]

In the ideal scenario where all resource types have perfect detection and travel at the same speed, the optimal allocation will follow probability density alone. Therefore *r* is the expected proportion of cells one would have to search before finding the subject, and *R* is the proportional gain over random searching. Because there is a great deal of uncertainty in search, scoring a single case is not very informative. *R* only becomes meaningful when it is calculated for many cases, to compare the average performance of different models on a fixed set of cases at a fixed resolution and extent.

Clearly, *R* is sensitive only to rank order, and not to the relative probability. Therefore, the actual values may be converted to a suitable grayscale image using any visually pleasing monotonic transform, and the scoring can be done directly on the image. However, the bit depth of the image will limit the number of possible distinctions: an 8-bit grayscale image has at most 256 possible values, and a 16-bit grayscale image has 65,536.

2.3 Scoring Methodology:

We use the format defined for the MapScore website.[4] Each map is a 5001 x 5001 grayscale raster centered on the IPP. Each pixel is 5m, resulting in a 25 x 25 km search area, which exceeds the 95% zone in almost all cases, and represents an upper bound on feasible ground searching. Models need not have 5m resolution internally, but they must convert their output to the standard format for scoring. MapScore uses 8-bit PNG

[3] Koester's correction matters in rule-based models where many pixels get the same value.
[4] http://mapscore.sarbayes.org

files, with lighter pixels representing higher probabilities.[5] If the 256 possible values were used equally, then each value would have about 98K pixels, and *R* would have a maximum value of .996.

R can be calculated offline, but using the website creates a public record and encourages comparison with other methods, potentially including subjective estimates. Users may select a case, receive the IPP and case information, and then upload a PNG image file with their probability map for that case. The website then scores the map using the actual find location, which is revealed along with the score. MapScore also allows batch submission via folders or zip files, so long as the individual maps are named to match the cases.

In the next section we discuss three relatively simple statistical models derived from the ISRID data, or the portions with good initial and find coordinates.

3. Data & Models

Koester (2008) organizes the ISRID cases into 41 categories & subcategories based on scenario, age, medical or mental status, and activity. Critically, he provides 25%, 50%, 75%, and 95% quantiles for the Euclidean distance between the IPP and the find location. Koester also provides summary statistics for elevation change, hours mobile, survivability, dispersion angle, and distance from nearest linear feature, when available. Where data permit, statistics are subdivided by domain (temperate, dry) and terrain (mountains, flat, and urban). The distance-ring model is the most widely used in WiSAR operations, and the best recorded.

Most of the ISRID cases do not contain usable GIS coordinates for both the initial and find locations. However, including the Yosemite data which became available during this study, 376 ISRID cases had reliable IPP and find coordinates. A third of the cases (89) are from New York, where a majority of the state is dominated by farms, forests, rivers, rolling mountains and lakes. It comprises the Northeastern Highlands, Erie Drift Plain, Eastern Great Lakes Lowlands and Atlantic Coastal Pine Barrens ecoregions(Bailey, R.G. 1995; Bryce, S.A. et al. 2010). A third were from Arizona (88 cases, transitional between plains and mountains), and

[5] MapScore may switch to 16-bit when participants start submitting higher-resolution models.

a third from Yosemite National Park, California (199 cases), a rugged valley between granite peaks in the Southern Sierra Nevada ecoregion (Bailey, R.G. 1995).

3.1 Distance Model

The Euclidean distance (ring) model is probably the most common model in statistical search planning. Dating back to Syrotuck (1976/2000), the model draws 25%, 50%, 75% and 95% distance rings based on statistical crow's-flight distance tables (Koester 2008). These distances correspond to the lower quartile, median, upper quartile, and 95th percentile of distance travelled by each category of lost persons in ISRID. As Table 1 shows, Koester's distance model considers terrain and ecoregion where the data permits.

Insert Figure 4 Here: Distance Rings Model

Insert Table 1 Here: Koester Hiker Table

Don Ferguson's IGT4SAR (Ferguson 2014; Ferguson 2013)[6] implements all of the distance-ring categories and subcategories from Koester (2008) in an ArcGIS toolbox. IGT4SAR extends the MapSAR[7] toolbox to include various elements of search theory. MapSAR is a free and open-source tool that runs with ESRI ArcGIS 10.X software[8] and enables maps to be generated, stored, and printed quickly in order for research teams to be able to perform faster searched for a missing person. (MapSAR and ESRI 2012)

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[6] https://github.com/dferguso/IGT4SAR
[7] http://www.mapsar.net
[8] http://www.esri.com/landing-pages/software/arcgis/arcgis101-trial, ESRI 2013. ArcGIS Desktop: Release 10.1. Redlands, CA: Environmental Systems Research Institute.

The IGT4SAR distance model uses the ArcGIS Multiple Ring Buffer tool to create four concentric rings centered on the IPP and representing the 25%, 50%, 75%, and 95% distances for this subject category and the terrain. The rings are created on a 50kmx50km region, and each ring is assigned the appropriate probability. The remaining 5% is assigned to the region outside the 95% circle. The five densities are then calculated by dividing each probability by the area of the corresponding region, and assigned to every pixel in the region. The model then clips the map to the 25x25km evaluation region.

3.2 Watershed Model

Although, the distance-ring model is an easy approach to use on a paper map, it ignores terrain. Terrain plays an important role in WiSAR. About ¾ of WiSAR incidents happen in the mountains, and mountains constrain travel. One simple way to account for terrain is to count watershed crossings (Doke 2012). Watershed boundaries follow ridge lines and unlike distance rings, reflect actual barriers to travel.

Insert Figure 5 Here: Watershed Model

In the United States, watersheds are delineated by the U.S. Geological Survey using a national standard hierarchical system that is based on surface hydrologic features and are classified into six units. The six main types of hydrologic units are region, sub-region, accounting unit, cataloging unit, watershed, and sub-watershed. Each hydrologic unit is identified by a unique hydrologic unit code (HUC) and consists of two to twelve digits based on the level of classification. For this paper a complete digital hydrologic unit boundary level of the sub-watershed (12 digit) 6^{th} level was used as a base map for the watershed model. The typical size for a 12-digit hydrologic unit is 10,000–40,000 acres; however, in some areas with unique geomorphology the watershed may be greater than 40,000 acres or less than 10,000 acres, but never less than 3,000 acres.

The sub-watershed (HUC-12) is the most detailed nationwide layer now available. ("Watershed Boundary Dataset" 2013)[9]

The watershed containing the IPP is numbered "0". All the watersheds on its border are numbered "1", "2", etc., so each watershed is assigned a number counting the minimum number of ridges between the IPP and the center of the watershed. We calculated watershed statistics from 398 historical cases as shown in **Error! Reference source not found.**. Each incident was classified as either "0", if found in the same catchment as the IPP, "1" if found adjacent, and so forth up to "3". Only 1 in 17 cases (about 6%) were found three or more watersheds away.

Insert Table 2 Here: Watershed Distance Statistics

Lastly, we divide the watershed-distance probabilities by the areas of all the watersheds at that distance, to get each region's *Pden*.[10]

3.3 Combined DW Model

A combined model may be made by simply "stacking" the two model layers, which is equivalent to a weighted average, or by calculating the actual joint probability distribution on the union of regions. The joint distribution will do better when the two models are not independent and there is enough data reliably to estimate the interaction. A combined model using the joint distribution of watersheds and Euclidean distance

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[9] The Watershed Boundary Dataset (WBD) and the National Hydrography Dataset (NHD) are coordinated efforts between the United States Department of Agriculture-Natural Resources Conservation Service (USDA-NRCS), the United States Geological Survey (USGS), and the Environmental Protection Agency (EPA). They were created from a variety of sources from each state and aggregated into a standard national layer for use in strategic planning and accountability. (http://nhd.usgs.gov/wbd_data_citation.html)

[10] Although this *Pden* method is correct on average, it could generate abnormal *Pdens* if, for example, the watershed-0 region was extraordinarily large (yielding too low a *Pden* near the IPP), or the watershed-3 region was clipped so as to be extraordinarily small (yielding a high *Pden* far away). A better method would be to calculate the average *Pdens* as part of the overall statistics, and apply those directly to each case.

was designed with the expectation that the model would do better than the two models taken separately, as is usually the case when combining estimates (Mattson 1980; Surowiecki 2005).

Figure 5 shows an example of the combined “Distance Watershed” (DW) model. The map regions are created by intersecting the distance rings and the watersheds (using the Union tool) so that a watershed cut by a distance ring becomes two new regions.

Insert Figure 6 Here: Combined Model Map

The probabilities for the combined DW regions are derived from the counts in Table 3. For example, Table 3 shows that the regions within the same watershed as the IPP and in the 50% ring only contained the lost person about in 61 out of 355 cases, or about 17% of the time.

Insert Table 3 Here: Distance Rings and Watershed statistics

The model then assigns a probability density by dividing the probability from Table 3 by the total area of all the polygons assigned that DW region in the map. For example, in Figure 7, the regions A, B, C and D constitute the (Watershed 1, 95% ring) region; each is assigned an un-normalized “probability” of 48/355 from Table 3, which is then divided by the combined area A+B+C+D. Now the watershed for region A also extends into the 75%, 50%, and even 25% rings. Although the probability of the (Watershed 1, 25% ring) region is only 9/355, the smaller area yields a higher *Pden*, shown by the darker shade.

Insert Figure 7 Here: Pden for Combined Model

4. Results

The Distance Ring model received an average score of approximately 0.780 (95%CI: 0.740 – 0.819). The Watershed model received a lower average score of 0.611 (95%CI: 0.572 – 0.650), and the combined model scored the highest with an average score of 0.805 (95%CI: 0.769 – 0.841). The Watershed model is clearly inferior to the other two. However, the Combined model is slightly better (two-tailed, paired T-test, N=376, t_{crit}=1.966, p=0.017).

Insert Figure 8 Here: Model Results

Despite largely ignoring local terrain, the ISRID distance ring model sets a high bar. Beating the ISRID distance model on our 5001-pixel-square images requires scoring solidly above about 0.8. By adding some very basic terrain information, the Combined model achieves improvements of about 6% of the original standard deviation, and about 11% of the possible gain.

There was also a regional influence. All models had their best performance in New York and their worst in Arizona where variance was also highest. The difference was statistically significant for both Distance and Combined models but not the Watershed model, which had poor performance in all three regions (F-crit = 3.02, F-value = 11.4, 8.6, 2.8; See Table 4.) Also, performance differences between models were statistically significant in New York and Yosemite, but not in Arizona (one-way ANOVA, F-value = 29.13, F-crit = 3.00). The combined model performed the best and with the least variance for the state of New York with an average score of 0.887 and variance of 0.059.

Insert Table 4 Model Mean and Variance by Region about here

5. Discussion

This study had four goals:

- Create a method and portal for scoring missing-person probability maps
- Score the ubiquitous ISRID Euclidean-distance "ring" model
- Compare the ring model to a new watershed model
- Compare those models to a combined distance-watershed model.

The results for the distance ring model were as expected. Based purely on ring geometry, the expected value of *R* for Hikers in a dry, mountainous domain is 0.78, closely mirroring the actual result (which was indeed mostly hikers in such environments). It was also anticipated that the distance ring model would score slightly higher in the state of New York than Arizona or Yosemite Park: because development and vegetation limit travel, the distance rings are closer in NY. (The temperate flat category has a 75% of 2km vs 4km for dry flat category).

The watershed model did worse than the ISRID distance rings, but performed surprisingly well considering that it ignores the subject category, environment, and climate (unlike the distance-ring model). It also scored higher in New York than in Arizona or Yosemite. The watersheds in our New York cases tend to be larger. Although Arizona has a lot of flat regions, most of the searches happened near the mountains, and the Arizona mountains are more rugged than the New York mountains. Yosemite, of course, is at least as rugged as Arizona.

It also helped that the New York IPPs were more likely to be somewhere in the center of a watershed, rather than on the ridge boundary, making the watershed distance parameter more reliable. When the IPP is on the dividing ridge, it is essentially random which side of the ridge will count as Watershed 0.

6. Conclusion & Future Work

The goal of any SAR operation is to increase the probability of success as quickly as possible with the available resources. Search and rescue activities rely heavily upon geospatial data, and GIS generation of the probability maps can speed search planning and generate better plans. However, while higher-resolution models including more factors will always seem more appealing, they need to be tested. MapScore provides access to a large set of historical missing-person cases, and a web portal for scoring and comparing models.

This paper publishes baseline scores for three relatively simple models: the commonly used ISRID Euclidean distance-ring model, a new watershed model which ignores subject category or terrain, and a combination of the two models. The watershed model by itself eliminated about 60% of the search area, but the familiar distance-ring model did better, eliminating over 75% of the search area. The combined DW model eliminated over 80% of the search area, even showing a statistical difference. All models did even better in New York and Yosemite, and worse in Arizona. Live GIS-based probability maps should improve key search planning decisions and increase situation awareness. Even if the GIS did not include automated resource assignment suggestions, the visual display of validated scenario-specific probability maps would be faster than drawing regions manually, and more accurate than intuitively sloshing probabilities into those regions. But the models tested here are only an automated manual method. GIS can do much more.

The next step is to explore parametric distance models[11] to remove the "jumps" in probability at the ring boundaries. Following that, improve the terrain model. One option is to refine the watershed layer. The HUC 12-digit watershed layer, although the most detailed currently available, has watershed regions that are too large for search purposes. A finer scale watershed layer may better capture the dynamics of movement and perform better. In addition, the watershed model should better account for IPPs on the ridge between the two watersheds, perhaps by assign ridge cases partially to all neighboring watersheds, or to a separate area.

[11] Forthcoming. See (Cawi 2014) for a preview.

If there is sufficient data available for the search region, another option is to augment watersheds with other travel barriers like streams and slopes, or skip simple barrier models entirely in favor of calculating travel cost surfaces. Preliminary tests of travel cost models showed the limiting factor was the quality of the available data layers. However, with effort a nationwide set could be synthesized for testing on MapScore.

Finally, these are all but steps along the way to defining actual motion models for SAR. We have not yet tested any motion models, though we are collaborating with other researchers to do so. Motion models have many parameters and assumptions, and without a good test suite like MapScore, they are difficult to evaluate.

MapScore has provided case data, a scoring metric, and a scored baseline. We invite contributions and hope within a year to see models scoring above 0.9.

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