AI for Infrastructure Monitoring

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Problem statement:

If state, local, and federal governments could monitor physical infrastructure with remote sensors, then they could plan replacement by optimizing resources and personnel. The US Army Corp of Engineers' Infrastructure Report Card rates domestic infrastructure with a "C-". Our roadways, resource networks, and broadband infrastructure is in a deteriorating state. An artificial intelligence system could help to prioritize maintenance by installing remote sensors that monitor structural integrity over time. AI for Infrastructure Monitoring refines target maintenance schedule precision to improve efficiency in infrastructure investments, so it can be marketed with the clever acronym: AIIM.

Training data:

Training the AIIM system will take time because infrastructure itself has a very long effective lifespan. There is also a wide variety of infrastructure types and functions across many environments and material types. Hoover Dam shares very little with a small bridge spanning a creek, but both have an effective lifespan before needing maintenance. For the purposes of this blueprint, we will focus on bridges for illustrative examples. Bridges and dams are easy to discuss in this context because they have a 0 to 1 fail state, whereas roadways and pipes experience slow degradation while still being used in a diminished capacity.

Training will proceed along two parallel programs. The first is a real world direct application isolated to a single city. We start by analyzing an inventory of bridges in the city and identifying which are nearing their estimated replacement date. Then, it's simply a matter of collecting sensor data to detect any pattern that would indicate fail-state structural integrity before the bridge reaches its official replacement date. The second program requires the development of a testing ground with the same sensors installed in bridges of different materials. Structures are then put through stress tests to simulate how much wear they can take until failing in a controlled environment.

X (input):

Input data for the AIIM system is measured by the relative distance traveled over time between an array of sensors installed at different locations throughout the structure. We should anticipate that sensors on a bridge that does not need replacement will record distance travelled that is statistically significantly smaller than a bridge nearing the end of its effective life. Distance traveled is an absolute term, not a relative proximity measure. Sensor points may drift apart then closer together over time, so measuring in a single direction would not be an effective input. The input data into the model is a cumulative measure point position change amongst the entire sensor network in a given bridge.

Y (output):

Output data for the AIIM system is a prediction of infrastructure maintenance. Current methods rely on engineering specifications and historical data. But if a bridge is still in good working order when its scheduled maintenance date comes around, it doesn't make sense to conduct repairs at that time. The same bridge might not be budgeted for repair or replacement when it is nearing the end of its effective lifespan, or it may not be checked again until it experiences a structural failure. Active real time sensors would create output data that would create an empirical measure to optimize budgeting and scheduling of maintenance for "just-in-time" solutions. The Y-label is effectively an automated decision to conduct maintenance or not which will empower city managers to optimize resources.

Y and Output discrepancies:

1) There may be other reasons to replace a bridge, such as nearby scheduled construction or capacity building. It is cheaper to combine projects, so if other construction is happening that affects the bridge in question, it's more effective to conduct maintenance on both even if a bridge in question still has useful years remaining.
2) There is a seasonal complication because freeze and thaw cycles cause bridges to expand and contract in a semi-regular pattern. This does add to wear on the bridge, but may cause noise in the signal intending to be captured.
3) A natural disaster like an earthquake or rare flood may damage a bridge. Certainly this will trigger sensors, but their effectiveness in prediction would be rendered useless since

the bridge would be replaced anyways. The signal that attaches the Y-label in this instance is, in the parlance of insurance adjusters, an act of god.

4) Movement between sensors may not be the only source that indicates structural integrity. If a spot between sensors gets worn out and falls away without causing movement, then the sensors will not transmit the necessary signal to trigger the meaningful Y-label.

The user thinks they're getting <Output> but is really getting Y:

1) The user thinks they are getting a resource optimization tool, but really they are getting something akin to an engine light. The salience of such an indicator will depend on how the system informs specific decisions within the engineering and finance departments.
2) The user thinks they are getting a predictor of physical maintenance, but really they are getting a system that reports changes in distance over time. If sensor location is not well chosen or if sensors fail, then the output will generate faulty Y-labels.
3) The user thinks they are getting a structural stability measure, but really they are getting, again, just a system that reports changes in distance over time. Depending on the materials, season, and region the fault tolerances of a given bridge may fall outside the triggering Y-label range. It is critical to work with structural and mechanical engineers when designing the AIIM system to set fault tolerances accurately.

Observations in the training data:

As mentioned above, training the AIIM system will take time and considerable startup cost to fully implement. Observations in the training data will be limited initially, but grow over time as more applications and scenarios get tested. Let's evaluate both training programs separately:

1) A pilot program targeting older bridges in a single city will produce observations specific to a single location and possibly represent build standards in that city that may not apply elsewhere. The ideal result from the pilot program is sensor output matching or contradicting the scheduled lifespan of different bridges followed by a physical inspection that confirms the sensor output/ Y-labels. But the design and installation of the sensors must be carefully considered to ensure that they report consistent and reliable

data. If there is telemetry interference or damage to the sensors, they will produce lower quality data.

2) A testing ground site will be very expensive to build and maintain, but it could be pitched as a generalized engineering research center for other applications besides just the AIIM system. The testing ground and pilot programs may suffer from a selection bias because they are targeted at subjects that are known to be waning in effective lifespan or being directly stressed to produce wear.

Observations in the deployment data:

Observations in the deployment data will include bridges outside the pilot program, made of various materials & designs, and located in different regions. Moreover, we want AIIM to be applicable to more than just bridges or dams. Infrastructure like water pipes, telecom wires, surface roads, or any number of other critical infrastructure should be able to benefit from the AIIM system in later iterations. Nation or even state level deployment should aspire to a scale beyond 0-1 fail state structures. So the regression analyses performed by the predictive AI will need to be modulated to measure input data from various types of sensors monitoring a wide range of structures and materials. Sensors will be exposed to the elements in different scenarios, so there will always be an uncertainty factor in the real world.

Observations and X-Y relationship discrepancies between training and deployment data:

1) Deployment data will have to include structures that are early in their effective lifespan.
2) Deployment observations in later iterations will include structures of different types of infrastructure, in different regions, and built by many construction companies.
3) Deployment data will be gathered from sensors exposed to potential interference from wildlife, vandalism, and acts of god. This extra cost calls into question the budget requirements for maintenance of the monitoring system.
4) The X - Y relationship discrepancies between training and deployment data are also confounded by selection bias. I believe that this can be overcome through expansion of the program, but since the startup costs are already huge and ROI is a multi-year or decade prospect, it will take considerable time to build out the system to critical levels.

5) As more structures come online in the deployment data, more variability will be introduced. Structures of different age, material, and design across different regions and engineering standards will further confound data normalization. Moreover, an increase in the number of monitored structures will also increase the relative propensity for them to be damaged by acts of god.

Functionality problems created X - Y relationship discrepancies:

Functionality problems in the AIIM system are essentially signal-to-noise errors from different sources. Remote sensing will always carry an uncertainty factor because telemetry and reliability can be affected by the environment. Choices regarding manufacture and installation will affect data quality and availability. Program design choices, particularly around fault tolerances, will affect measurement precision across different structure types and materials. Training data will remain limited in these capacities in the short run, and may not achieve reliable enough results to justify full deployment. To produce statistical significance within a realistic budget constraint, testing would need to be conducted with some element of selection bias and a small number of input variables.

Data ownership is yet another confounding factor. Local governments are in the best position to identify failing infrastructure, but lack the resources and/or authority in most cases to finance maintenance or alterations like remote sensors. A private firm or well-resourced public research institute would need to build the sensors and develop the technical aspects of the system. Procurement and contracting add another layer of complication and further uncertainties about data ownership that may negatively affect data fidelity as it passes between organizations. Local governments working in the implementation layer will want to address site specific infrastructure, but finance and researchers will want to work at scale to justify investing in the project development. Expanding the program to untested infrastructure types will reduce the statistical significance of any results AIIM may produce.

Algorithm deployment predictions:

AI for Infrastructure Monitoring was inspired by the book A New City O/S: The Power of Open, Collaborative and Distributed Governance, in which the authors envision ways in which technology and innovation can revolutionize public administration. The AIIM algorithm will take considerable start up time and costs, but will hopefully develop into a system that can accurately predict when infrastructure should be repaired or replaced. The Y-label in this scenario is an alert to an engineer that motivates an field inspection of a particular structure. Y-hat, as it were, is an approximation of structural integrity represented by a regression that measures distance traveled between a network of remote sensors over a given time period. This Y-hat prediction presumes that relative movement between sensors is a valid input parameter, but that may not be fully indicative in all cases. Some designs or materials will have different fault tolerances for instance, so the specificity of the AIIM system will take extensive testing in controlled settings to evaluate various scenarios properly. However, given what we already know about structural engineering and physics, there may be ways to close knowledge gaps more quickly and with lower start up costs.