

INTRODUCTION

- Reports of AI's influence range from wonderful to existential evolving impact on specific industrial sectors and society is far from clear
- History as a guide predictions tend to be wrong
- > Attempts to use AI to improve GNSS technological performance
- > Specific AI algorithms successfully used to make specific improvements
- > Slow introduction of AI in GNSS and PNT compared to other fields of geomatics
- > Trends summarized
- > Recommendations provided



GLOBAL NAVIGATION SATELLITE SYSTEM LABORATORY

- > Established in 2006 in Geomatics Engineering at Department of Earth and Space Science and Engineering
- > Professor Bisnath has 30 years of GNSS research and applications experience
- > GNSS measurement error mitigation
- ➤ GNSS **measurement processing** for positioning, navigation and timing (**PNT**)
- > Sensor fusion
- Scientific / engineering / mass market applications
- > PNT resilience
- > Application of **AI**



EXISTING AND CHANGING "DUALITY" OF GNSS USAGE



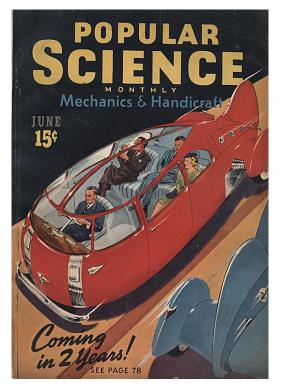


Geodetic (professional)Mass-marketMass-marketAll signal trackingMany signals trackedGPS L1 C/A-codeHigh-accuracyAccurate, low-costLow-costOpen skyEverywhereEverywhere

(Bisnath, 2020, IEEE/ION PLANS)

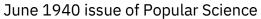


AUTONOMOUS AUTOMOBILE PREDICTIONS ...





https://clickamericana.com/topics/science-technology/future-predictions-from-mid-20th-century-retro-futurism



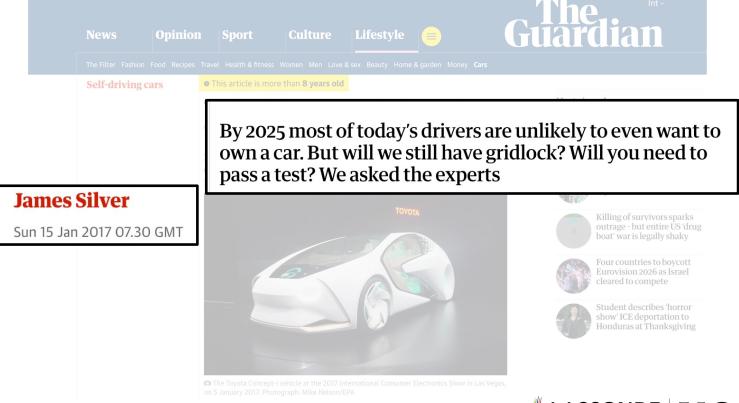


AUTONOMOUS AUTOMOBILE PREDICTIONS ...





AUTONOMOUS AUTOMOBILE PREDICTIONS ...





AUTONOMOUS AUTOMOBILE AND AI PREDICTIONS

The current state of the Al debate:



On-line meme, Why Tech Predictions Always Miss the Mark | Ignacio Ramirez Moreno



AUTONOMOUS AUTOMOBILE AND AI PREDICTIONS

The current state of the Al debate:



On-line meme, Why Tech Predictions Always Miss the Mark | Ignacio Ramirez Moreno



AUTONOMOUS AUTOMOBILE AND AI PREDICTIONS

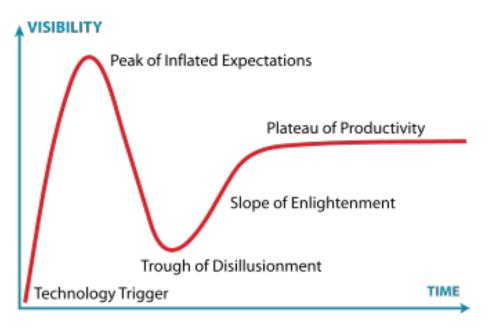
The current state of the Al debate:



On-line meme, Why Tech Predictions Always Miss the Mark | Ignacio Ramirez Moreno



NEW TECHNOLOGY DEVELOPMENT CURVE



https://en.wikipedia.org/wiki/Gartner_hype_cycle

Gartner hype cycle: graphical representation of maturity, adoption and social application of specific technologies

Hype cycle's veracity disputed, with studies pointing to it being inconsistently true at best



NEW TECHNOLOGY DEVELOPMENT CURVE



https://en.wikipedia.org/wiki/Gartner_hype_cycle

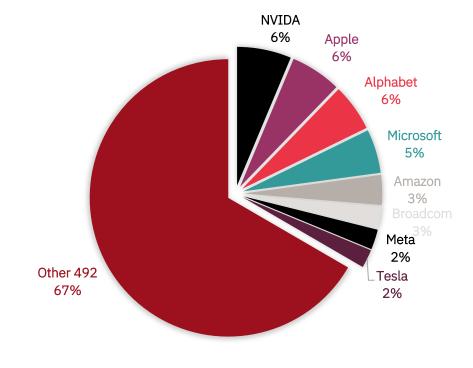


https://techcrunch.com/2012/04/01/the-market-curve-the-life-cycle/



TOP OF THE STOCK MARKET

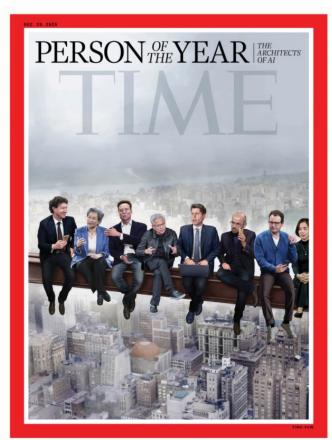
Company	Market capitalization (Trillions USD)
NVIDA	6.2
Apple	5.8
Alphabet	5.4
Microsoft	5.0
Amazon	3.4
Broadcom	2.5
Meta	2.3
Tesla	2.1
Other 492	65.3
TOTAL	98



Largest companies by market capitalization S&P 500 - Dec 4th, 2025







Painting by Jason Seiler for TIME



OMINOUS PREDICTIONS FOR AI



https://www.unite.ai/has-ai-taken-over-the-world-it-already-has/



NEGATIVE AI EFFECTS IN RESEARCH

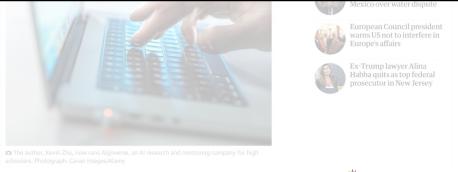






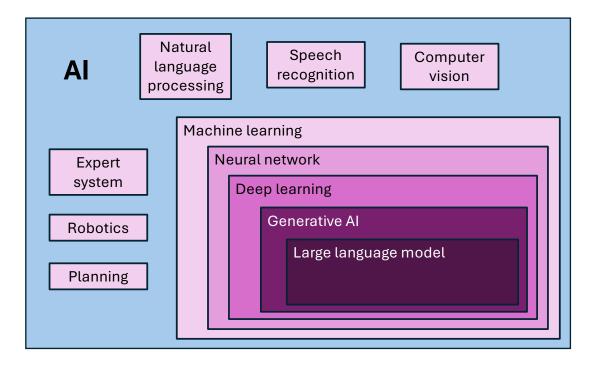
NEGATIVE AI EFFECTS IN RESEARCH







CONCEPTS WITHIN / SUBSETS OF AI



(Bisnath, 2025, GPS World)



TYPES OF MACHINE LEARNING MODELS

AND TRAINING ALGORITHMS Unsupervised **Supervised** Semi-supervised learning learning learning Builds a model through Data scientists provide Use deep learning to input, output and arrive at conclusions a mix of labeled and feedback to build model and patterns through unlabeled data, a set of (as the definition). unlabeled training data. categories, suggestions and exampled labels. **EXAMPLE ALGORITHMS:** EXAMPLE ALGORITHMS:

Apriori

- Sales functions.
- Word associations.
- Searcher.

K-means clustering

- Performance monitoring.
- Searcher intent.

Artificial neural networks

- Generate new, synthetic data.
- Data mining and pattern recognition.

EXAMPLE ALGORITHMS:

Generative adversarial networks

- Audio and video manipulation.
- Data creation.

Self-trained Naïve Baves classifier

 Natural language processing.

Reinforcement learning

Self-interpreting but based on a system of rewards and punishments learned through trial and error, seeking maximum reward.

EXAMPLE ALGORITHMS:

Q-learning

- Policy creation.
- Consumption reduction.

Model-based value estimation

- Linear tasks.
- Estimating parameters.

Ensemble learning

Combination of other models.

https://www.techtarget.com/searchenterpriseai/tip/Types-oflearning-in-machine-learning-explained





Linear regressions

comparison.

Decision trees

Pricing.

Sales forecasting.

Risk assessment.

Support vector machines

Image classification.

Predictive analytics.

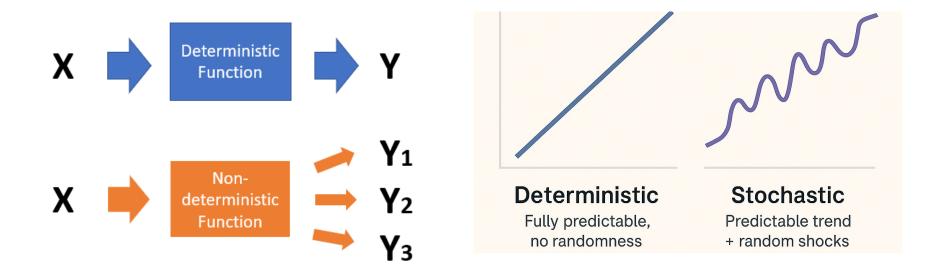
Financial performance

WHY THE SLOW ADOPTION OF AI IN GNSS?

- Over past decade:
 - ML has been adopted in, and has transformed, many areas of Geomatics
 - e.g., photogrammetry, remote sensing, GIS
 - And merged with computer science approaches, e.g., computer vision, SLAM, geospatial data analytics
- > Classical PNT optimal estimation techniques have served GNSS community well
- GNSS problems tend to be "well-defined" and "well-behaved" compared to other Geomatics problems
- Geodesists have long history of physics-based solutions resistance to AI



DETERMINISTIC VERSUS NON-DETERMINISTIC VERSUS STOCHASTIC



https://www.statisticshowto.com/deterministic-function-nondeterministic/

https://www.linkedin.com/pulse/why-arima-models-always-carry-error-term-vs-explained-krish-naidu--sgtuc



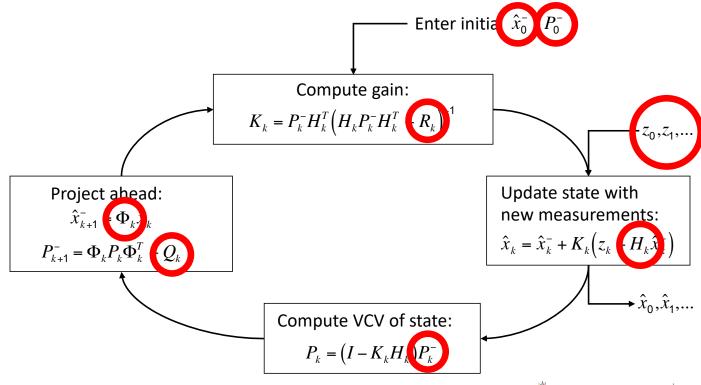
HOW ARE WE MODELLING MEASUREMENTS IN GNSS?

$$P_{r,1}^{s}(t_{r}) = \rho_{r}^{s}(\hat{t}^{s}) + c(dt^{s} - dt_{r}) + dT_{r}^{s}(t_{r}) + dI_{r,1,p}^{s}(t_{r}) + dm_{r,1,p}^{s} + dh_{1,p}^{s} + dh_{r,1,p}^{s} + \varepsilon_{1,p}$$

$$\Phi_{r,1}^{s}(t_{r}) = \rho_{r}^{s}(\hat{t}^{s}) + c(dt^{s} - dt_{r}) + dT_{r}^{s}(t_{r}) - dI_{r,1,\Phi}^{s}(t_{r}) + \lambda_{1}N_{r}^{s} + dm_{r,1,\Phi}^{s} + dh_{1,\Phi}^{s} + dh_{r,1,\Phi} + \varepsilon_{1,\Phi}$$

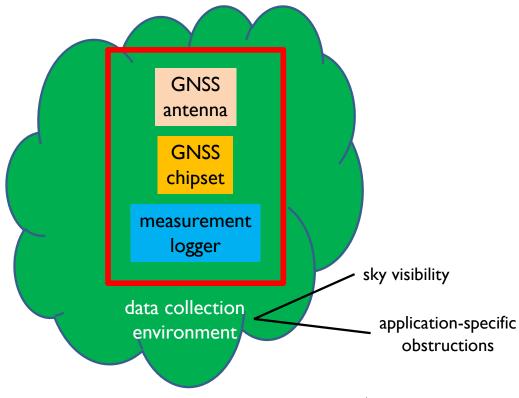


HOW ARE WE ESTIMATING UNKNOWN STATES IN GNSS?





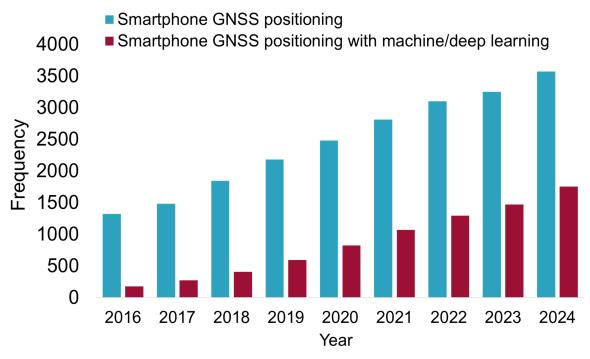
OVERALL PROBLEM STATEMENT FOR SMARTPHONE GNSS MEASUREMENTS



(Bisnath and Aggrey, 2024, ION ITM)



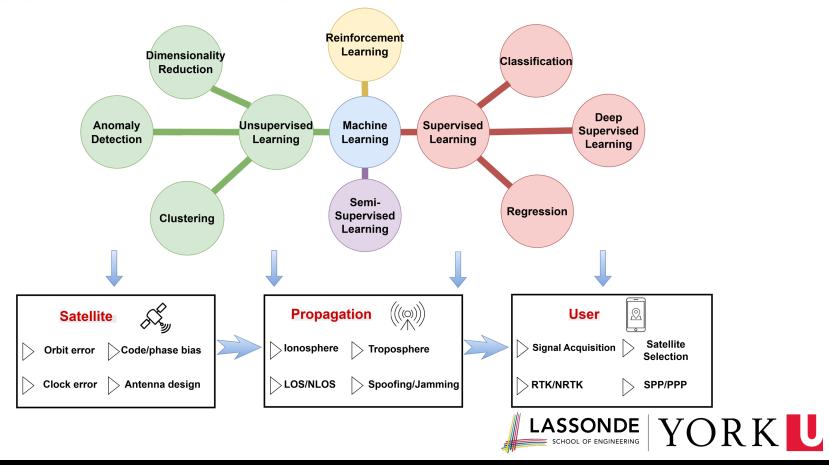
GROWTH OF SMARTPHONE GNSS ML PUBLICATIONS



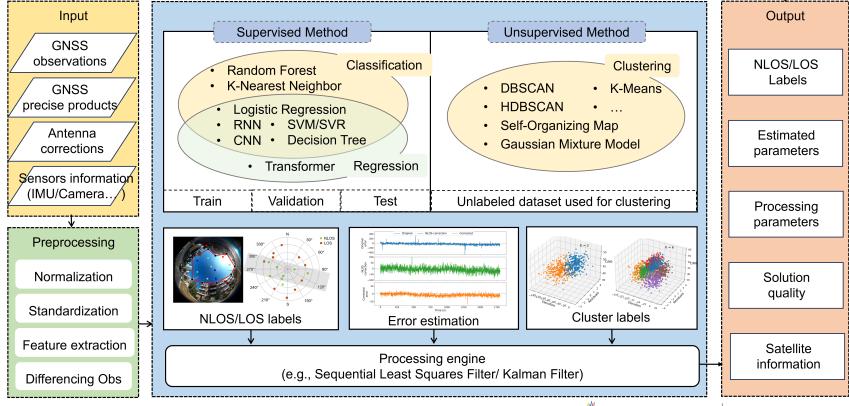
Keyword frequency on Google Scholar, 2016-2024 Data retrieved on: 9th Jun 2025



OVERVIEW OF ML METHODS AND USE CASES IN GNSS SMARTPHONE POSITIONING



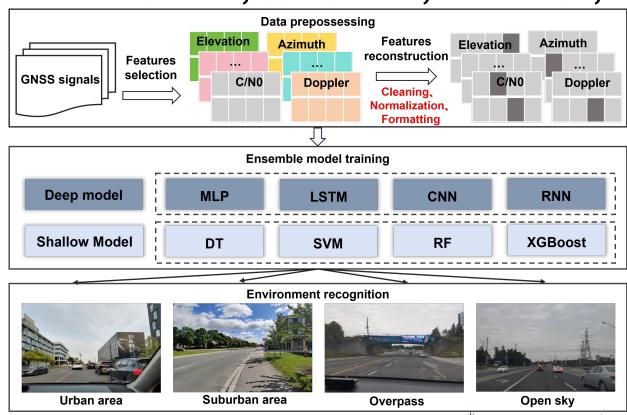
STRUCTURE OF DIFFERENT ML ALGORITHMS USED IN **GNSS PPP NLOS/MULTIPATH CLASSIFICATION**





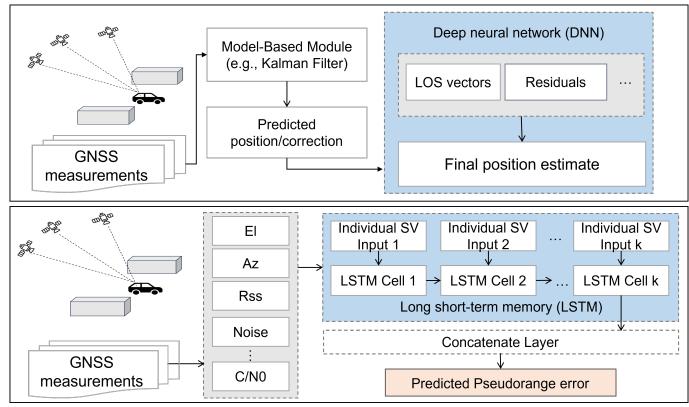


ML-BASED RECOGNITION OF GNSS RECEPTION ENVIRONMENTS: URBAN, SUBURBAN, OVERPASS, OPEN-SKY





COMPARISON OF ML APPROACHES FOR POSITION AND OBSERVATION DOMAIN CORRECTION

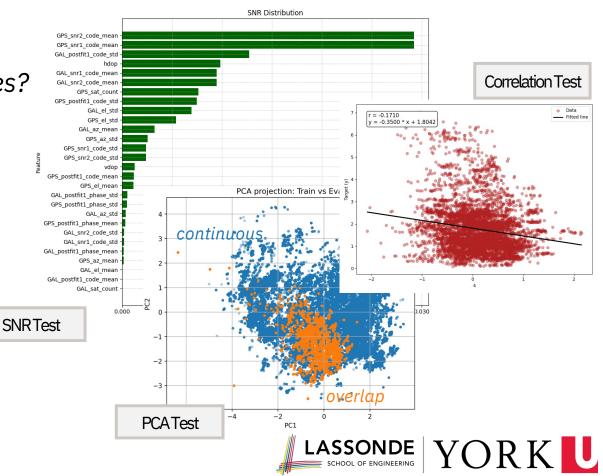




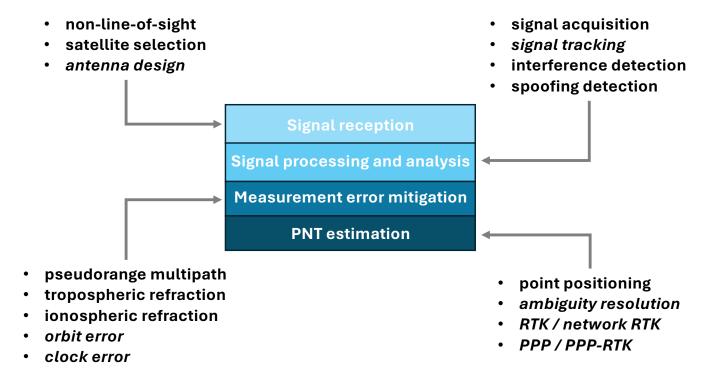
FEATURE ENGINEERING

What makes good features?

- Correlated with targets
- Low redundancy
- Good stability
- · Reasonable distribution
- Significant



APPLICATION THEMES OF MACHINE LEARNING IN GNSS WITH INITIALLY STUDIED AND *POTENTIAL* RESEARCH AREAS



(Bisnath, 2025, GPS World)



RESOURCE CONSIDERATIONS FOR MACHINE LEARNING USE IN GNSS

Resource consideration	
Applicability / reliability	
Significance of improvement	
Data availability	
Data storage	
Computing power	
Equipment and electrical power budgets	
Hardware and software implementation	

(Bisnath, 2025, GPS World)



SUMMARIZING AI IN GNSS TRENDS

- > Accelerating amount of research applying ML approaches to enhance GNSS-based PNT
- > Great deal of ineffective research
- We aren't developing AI algorithms, but we need to well understand how to use these tools – which requires significant insight
- > Specific, narrow improvements obtained, especially in:
 - LOS / NLOS / multipath classification
 - Interference detection
 - Ionospheric refraction prediction



WHERE ARE WE GOING?

- > Much more experimentation with ML algorithms and models
- > Optimal balance between specific measurement error mitigation and state estimation
- > Optimal feature engineering
- > (Hopefully) eventual convergence on "best" algorithms and models to use for specific purposes
- > General adoption of ML in specific applications



KEY CHALLENGES FOR ML USE IN GNSS

- > Finding "best" algorithms and models for each GNSS performance issue
- > Performance improvement versus costs (computational, power, complexity, etc.)
- > Estimating integrity
- > Certification of ML-based system solutions for safe-of-life applications



WHERE MAY WE END UP?

- Perhaps significant adoption of ML in particular aspects of GNSS measurement characterization
- > Perhaps significant adoption of ML in particular aspects of GNSS measurement processing
- Perhaps hybrid SLS or EKF estimation with ML used to model non-deterministic processes and deal with invalid optimization assumptions
- > More resilient, low-cost GNSS-based PNT



Thank you



Our people are our strength

gnsslab.lassonde.yorku.ca

