Data Science SONYC

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SONYC Data Science

- Analysis of SONYC data 34 years worth of data
- Analysis of SONYC together with multiple data sets
 - E.g.: How construction permits impact SPL captured by SONYC
- Data collected from traditional and *unsuspecting* sensors
 - SONYC, census, crime, building permits, public transportation, tweets

Opportunity: leverage this data to make new insights about how people are using cities, frame new policies and make cities more efficient





Challenges of Data Science

- SONYC: 34 years worth of data
 - How to handle and query large data?
 - How to visualize this data?
 - How to gain new insights from the data?





Objectives for SONYC

- Interactive querying of noise data
 - Techniques to support interactive, low latency queries of SPL data
 - Drive exploratory visualization
- Visual interface
 - Build a visual interface for noise data exploration
 - Explore noise in the context of the city and related data
- Analysis of city-wide noise
 - Data analytics to gain insights into possible patterns of noise over space and time
 - Use the generated data (SPL) together with open data
 - Generate a city-wide time-varying noise map























Objective

- Support queries having constraints at multiple time resolutions
 - Average SPL each hour of the day
 - Average SPL day of the week
 - Average SPL each day of the week, between 8am 6pm
- Support range queries at multiple resolutions
 - Average SPL between March 1st and March 15th, at hour resolution
- Support updates from new data





	Size		Q	1	Q2		Q3		Q4	
	(MB)	Overhead	Time(ms)	Speedup	Time(ms)	Speedup	Time(ms)	Speedup	Time(ms)	Speedup
Nanocube	41799	10349 %	116		4.6		2491.8		40083	
Pandas	1600	300%	1670		9355		10399		11070	
InfluxDB	412	3%	10574		42913		35259		29058	
TimescaleDB	7867	1866%	20385		60206		130594		101036	
KairosDB	1301	225%	229110		629886		240168		75267	





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- Support updates from new data
- Small memory overhead
- Allow low latency queries over large time series (< 1 second)





• Time Lattice

- Data structure that supports multiple resolution queries at interactive rates
- Makes use of the implicit hierarchy present in temporal resolutions to materialize a sub-lattice of a data cube





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Time Lattice	407	1.75%	40	-	15	-	12	-	92	-



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	(MB)	Overhead	Time(ms)	Speedup	Time(ms)	Speedup	Time(ms)	Speedup	Time(ms)	Speedup
Nanocube	41799	10349 %	116	2.9x	4.6	0.3x	2491.8	194x	40083	433x
Pandas	1600	300%	1670		9355		10399		11070	
InfluxDB	412	3%	10574	261X	42913	2860x	35259	2754x	29058	314x
TimescaleDB	7867	1866%	20385		60206		130594		101036	
KairosDB	1301	225%	229110		629886		240168		75267	
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Constant insertion time: ideal for streaming

Linear memory overhead





Handling Large Spatio-Temporal Data

- Developing a set of GPU-based techniques
- STIG [Doraiswamy et al. 2015]

Query	MongoDB	Postg	reSQL	Co	omDB
	Time	Time	Speedup	Time	Speedup
1	0.075	503.9	6718x	20.6	274x
2	0.080	501.9	6273x	23.3	291x
3	0.067	437.8	6534x	21.6	322x
4	0.070	437.1	6244x	32.6	465x





Time in Seconds

Handling Large Spatio-Temporal Data

• Raster join [Tzirita Zacharatou, Doraiswamy et al., 2017]















Time Lattice Interface: Noise Profiler



- Noise Profiler
 - Enable domain experts to specify, execute and visualize queries over the SPL data from across the city.
 - Compare data from one or more sensors
 - Support multiple metrics as the aggregate in the queries (e.g. equivalent continuous A-weighted sound pressure level)



Time Lattice Interface: Noise Profiler







Time Lattice Interface: Noise Profiler













Analysis of after hour variances

THE REAL DEAL New York Miami Los Angeles

Q Search

April 2016 Issue

The after-hours construction boom

Why buildings are rising on nights and weekends

By Kathryn Brenzel | April 01, 2016 12:00PM

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(Photo: Shutterstock)



NEW YORK POST

Buildings Dept. approves night construction, angering residents

By Isabel Vincent and Melissa Klein

January 31, 2016 | 1:51am



Shuttersto



Analysis of after hour variances









Find spatio-temporal relationships

- Data Polygamy [Chirigati et al., 2016]
 - 100's of spatio-temporal data sets
 - Relationships occur only over certain points in space and time
 - Millions of possibilities
 - How to efficiently identify interesting relationships?







Quantify and compare "activity"

- Urban Pulse [Miranda et al., 2017]
 - Signature for different locations
 - Data oblivious
 - Rank and compare locations
 - Query similar locations

Rockefeller Center





Union Square



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Alcatraz





Analysis of sound propagation

- Potential approach
 - Make use of highly detailed building models available in NYC
 - Use ray tracing to propagate sound over time
- Initial technology already in place [Miranda, Doraiswamy et al., 2018]
 - Interactively compute shadow accumulation over time
 - Makes use of accurate 3D geometry
 - Uses GPU for efficient ray propagation





Quantifying shadow

Shadow accumulation





[Mapping the Shadows of New York City - The New York Times]



Quantifying shadow

Shadow accumulation











Quantifying shadow

- Shadow accumulation
 - Uses ray tracing to accumulate shadow over time
 - Allows for interactivity
 - Analysis of shadow impact from proposed buildings on public spaces



[Miranda, Doraiswamy et al., 2018]







Outcomes

• Papers:

Published:





Eurovis

- Open source projects:
 - Raster Join: github.com/ViDA-NYU/raster-join
 - Urban Pulse: github.com/ViDA-NYU/urban-pulse
 - Time Lattice: soon

• Media coverage





New York Times

Thank you!

The Economist

R Q N) HEREFORM THE REPORT Urban Pulse Uses Social Media Data to Show Cities in a New Light The sper source platem candid none work for uchlises and planmers resing a befor inclusion of places and be pupply who are then.



Architecture Digest



Curbed



