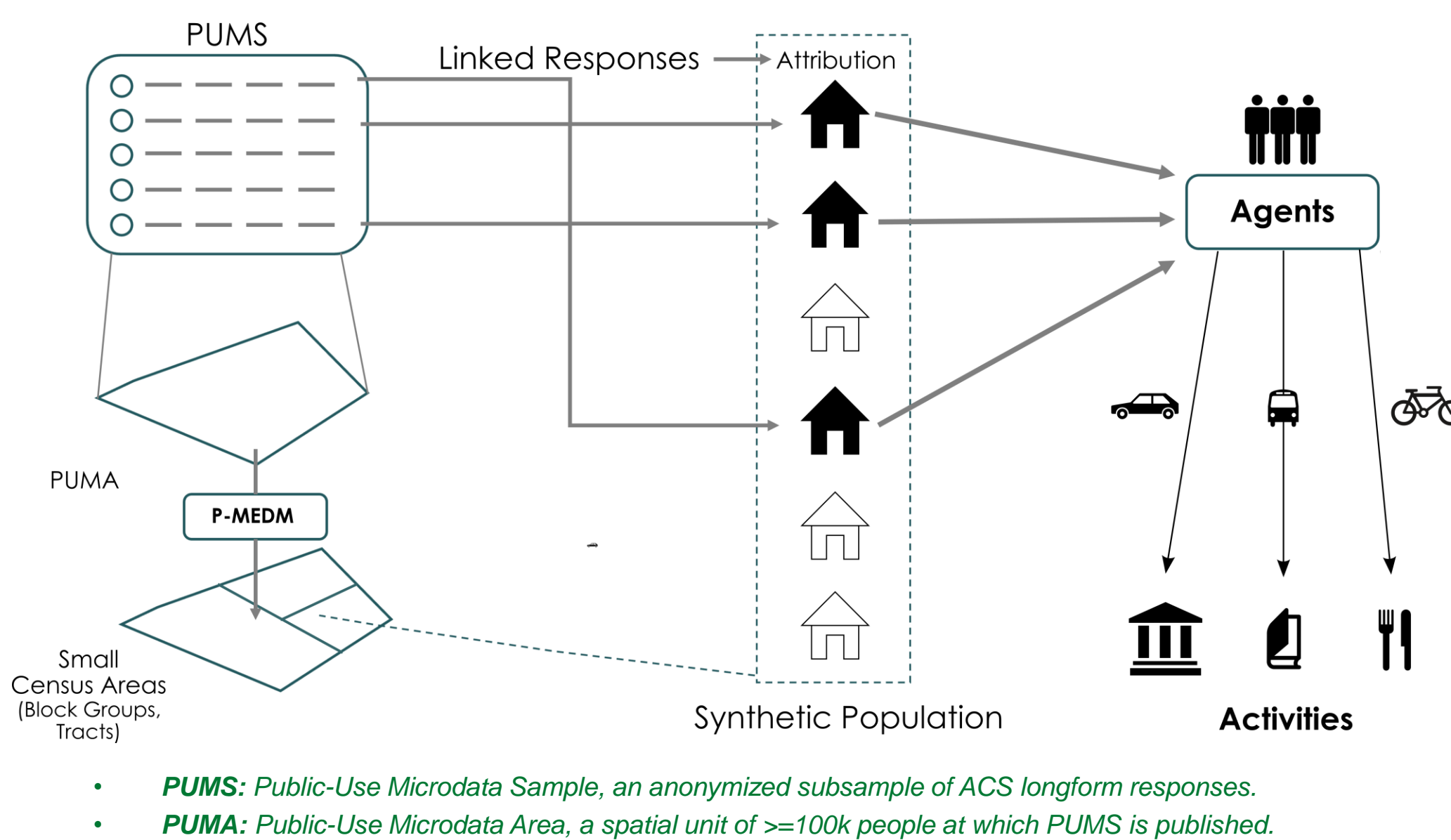


Vivid Synthetic Populations for Human Dynamics Models

- Security and social equity issues within human systems → human dynamics: *how people live, move, and interact*
- Likeness toolkit → human dynamics + vivid (attribute rich) synthetic populations from American Community Survey (ACS)
- Supports the creation of more dynamic agent-based models (ABMs) for topics from epidemiology to environmental hazards



- PUMS:** Public-Use Microdata Sample, an anonymized subsample of ACS longform responses.
- PUMA:** Public-Use Microdata Area, a spatial unit of $\geq 100k$ people at which PUMS is published.

Validation Exercise

How well does Likeness recreate demographic estimates:

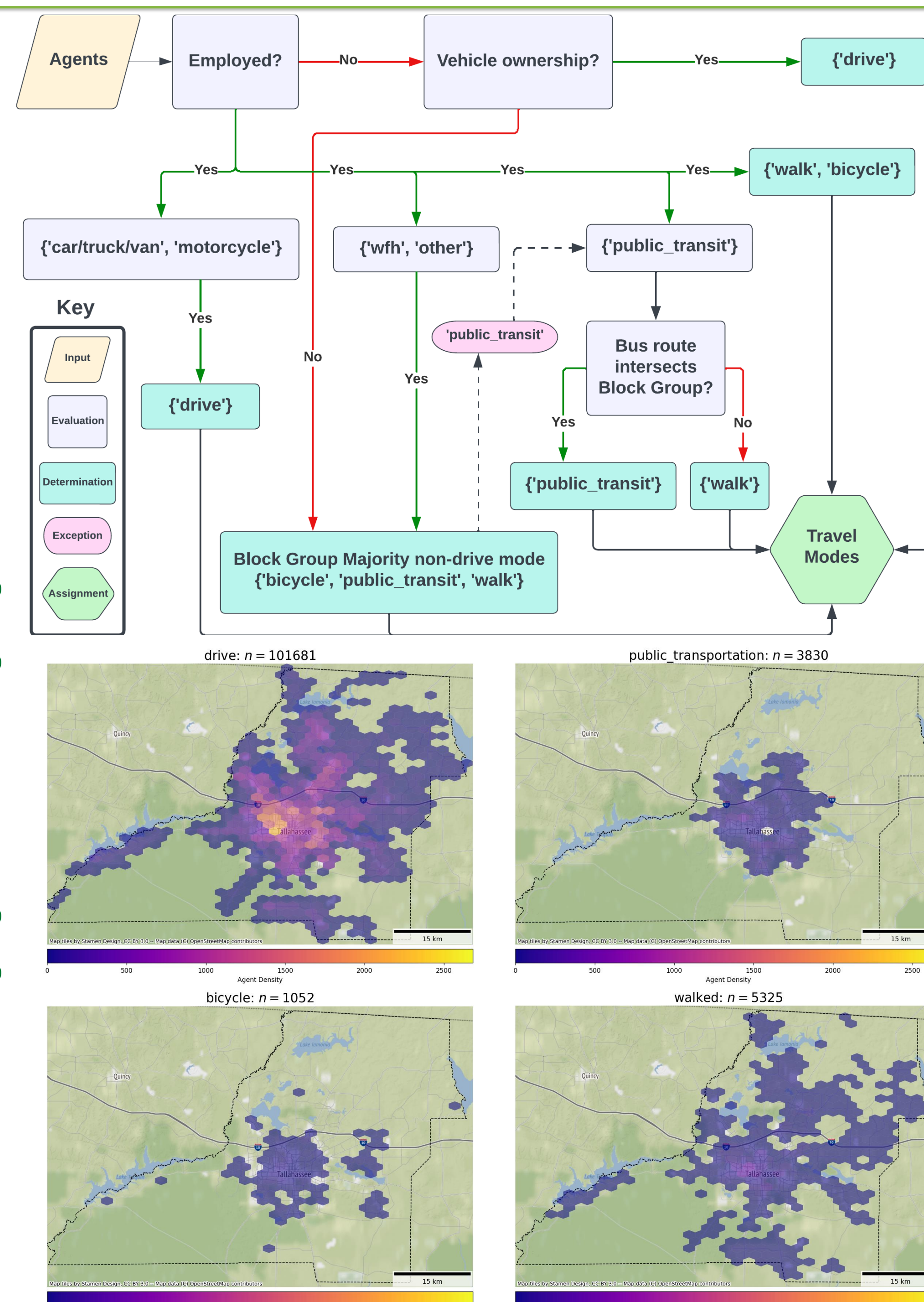
- Based on neighborhood residential characteristics?
- For essential activities? (e.g., social, errands, health)

Case Study: Leon County, FL

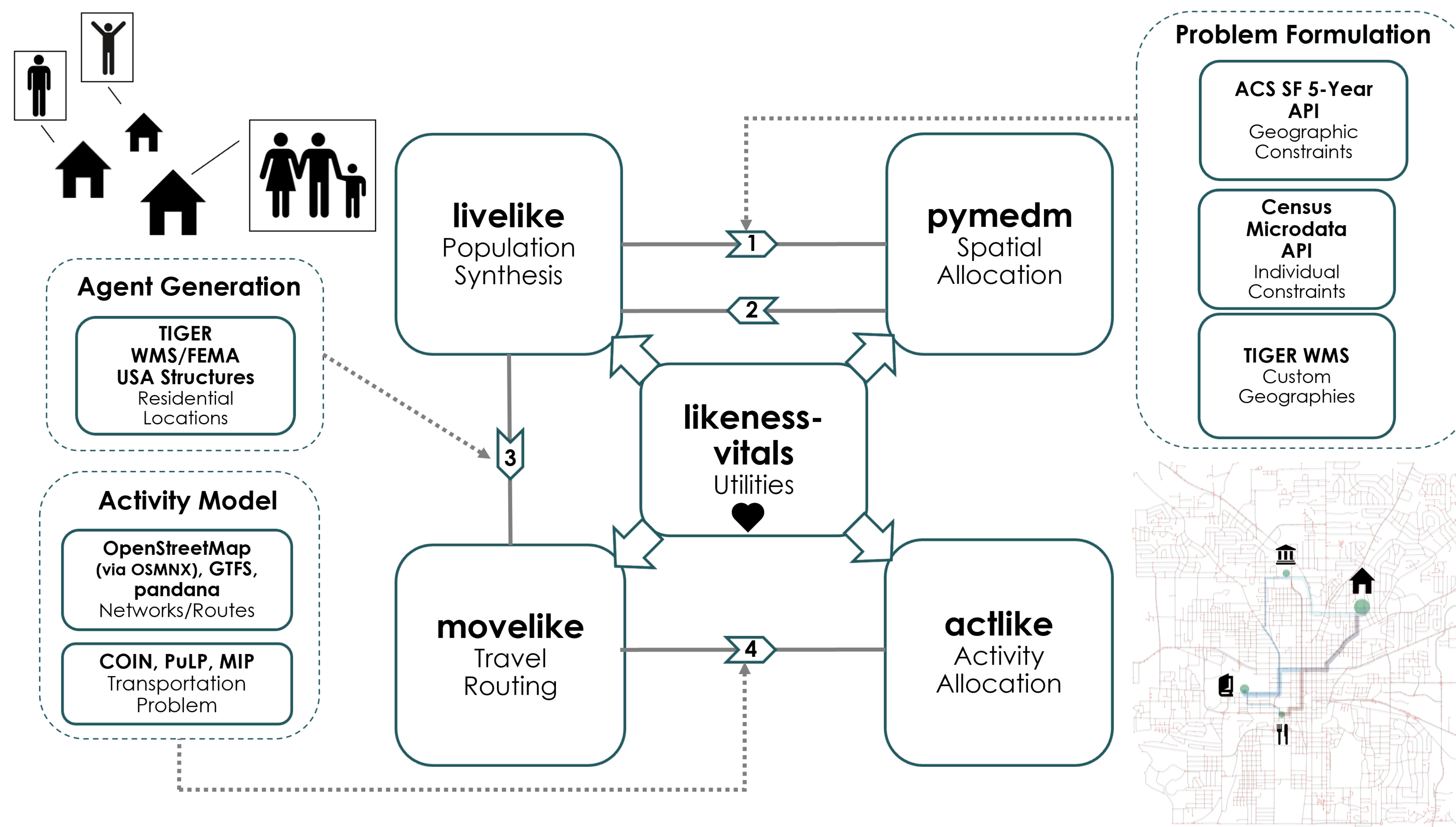
- Compact urban footprint (Tallahassee), multiple travel modes
- Single synthetic population realization based on ACS 2019 5-Year Estimates
(**Constraints:** population, built environment, socio-demographics, economic status workforce, students)
- Essential service (grocery store) visits by age/gender
(**Source:** Foursquare Places/Visits)

Public Domain image from Wikimedia Commons

Locating Agents and Assigning Travel Modes



An Evolving Ecosystem



Key improvements

- Population synthesis workflow for any Metropolitan Statistical Area (MSA) in the US
- GPU-enabled spatial allocation modeling with pymedm (via jaxopt)
- Simulated residential locations for routing trips to essential activities (livelike)
- Dedicated support for transportation networks, incl. transit routes (moveLike)
- Shared utilities for process management, data manipulation, post-processing (likeness-vitals)

Into the Future

- Open-sourcing** the software stack, beginning with pymedm
- Packaging schema:** toward a monolithic Likeness package with submodules
- Creating a dedicated package for **visualization** functionality
- Improving mobility modeling**, particularly realistically representing public transit networks
- Solving the optimization bottleneck for large scale transportation problems** by profiling existing methodology or exploring high-efficiency solvers

Recommended Resources

- Birkin, M. & Clarke, M. (2011). Spatial Microsimulation Models: A Review and a Glimpse into the Future. In: Stillwell, J., & Clarke, M. (eds) *Population Dynamics and Projection Methods. Understanding Population Trends and Processes*, vol 4. Springer, Dordrecht. DOI: 10.1007/978-90-481-8930-4_9.
- Harland, K., Heppenstall, A., Smith, D. & Birkin, M.H. (2012). Creating realistic synthetic populations at varying spatial scales: A comparative critique of population synthesis techniques. *Journal of Artificial Societies and Social Simulation*, 15(1):1, DOI: 10.18564/jasss.1909.
- Morton, A.M., J.O., Nagle, N.N., Aziz, H.M., Duchscherer, S., & Stewart, R.N. (2017b). A simulation approach for modeling high resolution daytime commuter travel flows and distributions of worker subpopulations. In *GeoComputation 2017*, pp. 1–5, Leeds, UK.
- Nagle, N.N., Battenfield, B.P., Leyk, S., & Spielman, S.E. (2014). Dasymetric modeling and uncertainty. *Annals of the Association of American Geographers*, 104(1):80–95, DOI: 10.1080/00045608.2013.843439.
- Tuccillo, J.V. & Gaboardi, J.D. (2022, June). Likeness: a Python toolkit for connecting the social fabric of place to human dynamics. *GeoPython 2022*. DOI: 10.5281/zenodo.6685086.
- Tuccillo, J.V. & Gaboardi, J.D. (2022). Likeness: A toolkit for connecting the social fabric of place to human dynamics. In Agarwal, M., Calloway, C., Niederhut, D. & Shupe, D. (Eds.), *Proceedings of the 21st Python in Science Conference* pp. 125–135, DOI: 10.25080/majora-212e5952-014.
- Tuccillo, J.V., Stewart, R.N., Rose, A., Trombley, N., Moehl, J., Nagle, N.N., & Bhaduri, B. (2023) UrbanPop: A spatial microsimulation framework for exploring demographic influences on human dynamics. *Applied Geography*, 151, pp. 102844, DOI: 10.1016/j.apgeog.2022.102844.

Results

Neighborhood Demographics

- All synthetic block group estimates of model constraints preserved at least 90% of the ACS Summary File (SF) constraints.
- Performance weaker in areas with large group quarters populations (college dormitories, prisons), low density/rural areas.

Essential Activities

- Mixed performance for within-POI demographic composition (synthetic vs. observed).
- Performance generally improves in central areas of Tallahassee (pictured) and weakens along Leon County's urban fringe.
- Could spatial factors like activity density, diversity of travel modes influence this?