

DYNAMIC DISCRETE CHOICE MODELING

FOR CAR USE, OWNERSHIP AND FUEL TYPE BASED ON REGISTER DATA

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- Introduction
- The data
- Possible approaches
- The dynamic discrete choice model
- Value iteration results
- Conclusion and future works

Aim of the research project:

- Model dynamics of car transactions, usage and choice of fuel type in the Swedish car fleet
- Motivations
 - Governmental policies (Source: Swedish parliament):
 - Goal of fossil-independent vehicle fleet by 2030
 - No emissions by 2050
 - Technology changes:
 - Increase of alternative-fuel vehicles
 - Changes in the supply
 - Company cars: represent important share of new car sales
- Difficulties
 - Car are durable goods \implies modeling transactions not straightforward
 - Need to account for forward-looking behavior of individuals

Current literature on car ownership and usage modeling:

- **Car ownership models in transportation literature:**
 - Mostly **static models**:
 - Main drawback: do not account for forward-looking behavior
 - Important aspect to account for since car is a durable good
 - **Econometric literature: dynamic programming (DP) models**
 - Recently, **dynamic discrete choice models (DDCM)** starting to be applied in transportation field (Cirillo and Xu, 2011; Schiraldi, 2011)
- **Other types of joint models of car ownership and usage:**
 - **Discrete-continuous model** of vehicle choice and usage based on register data (Gillingham, 2012)
 - **Duration models** and regression techniques for car holding duration and usage (De Jong, 1996)

Register data of Swedish population and car fleet:

- Data from 1998 to 2008
- All individuals
 - **Individual information:** socio-economic information on car holder (age, gender, income, home/work location, employment status/sector, etc.)
 - **Household information:** composition (families with children and married couples)
- All vehicles
 - Privately-owned cars, cars from privately-owned company and **company cars**
 - Vehicle **characteristics** (make, model, fuel consumption, fuel type, age)
 - **Annual mileage** from odometer readings
 - Car bought **new or second-hand**

Advantage of such detailed data:

- Can observe and analyze **demand shifts** that occurred as a response to changes in policies:
 - Changes in vehicle circulation taxes
 - Changes in fuel prices
 - Introduction of congestion pricing
- } at a national/regional level
- } at a local/regional level
- Can test the impact of **planned policies** on the demand for vehicles and car usage (e.g. fossil-independent fleet by 2030)

Aim of the project:

- Model simultaneously car ownership, usage and fuel type.
In details: model **simultaneous choice** of

$$\text{Transaction type} \times \left[\begin{array}{l} \text{Annual} \\ \text{milage} - \\ \text{car } c \end{array} \times \begin{array}{l} \text{Private/} \\ \text{company} \\ \text{car} - \\ \text{car } c \end{array} \times \begin{array}{l} \text{Fuel type} - \\ \text{car } c \end{array} \times \begin{array}{l} \text{New/2}^{\text{nd}} \text{ hand} - \\ \text{car } c \end{array} \right] \# \text{ cars}$$

- No more than 2 cars in household
- Account for forward-looking behavior of households

How can car ownership and usage be modeled?

Studied 2 approaches:

1. **Discrete-continuous dynamic programming:**
mileage(s) considered as continuous and other variables as discrete.
2. **Dynamic discrete choice modeling:**
all components of a choice variable are discretized.

How can car ownership and usage be modeled?

1. Discrete-continuous DP

- **Endogeneous grid method (EGM)** to solve continuous choice problems (Carroll, 2006) in a fast way: avoids a numerical rootfinding procedure when the Euler equation is solved
- EGM **generalized for discrete-continuous** choices (Iskhakov et al, 2012). Valid when one continuous variable is considered.

How can car ownership and usage be modeled?

2. DDCM

- All variables considered as discrete \Rightarrow mileage(s) discretized
- In transportation research, DP methods using **random utility theory** developed for **discrete actions**
 - Account for random term in utility function
 - Assumption that choices are affected by unobserved attributes, taste variations, etc.
- These DP methods lead to simple closed-form formula for the Bellman equation (e.g. Aguirregabiria and Mira, 2010)

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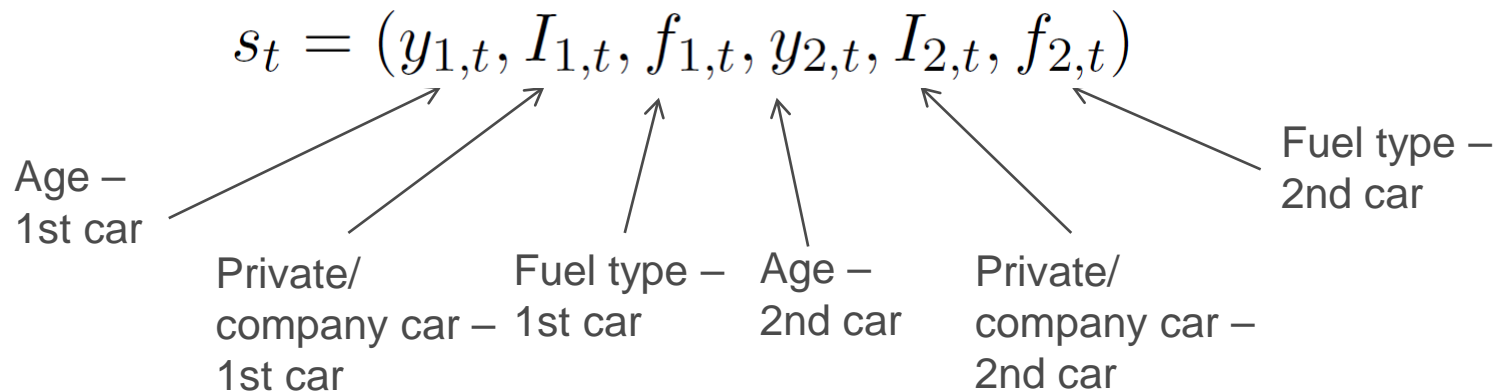
Approach selected

Motivations for DDCM

- In **transportation engineering**, usually work with **random term** in utility
- Though treating mileage as continuous is more adapted, **no work on discrete-continuous DP models accommodating random utility theory**
- Current DDCM were developed for a **different setting**:
 - Rust (1987) (and other applications) uses discrete actions and discretizes a continuous state space.
 - Here: large and discrete-continuous action space (while the state space is discrete and small)

Definition of the components of the dynamic programming model:

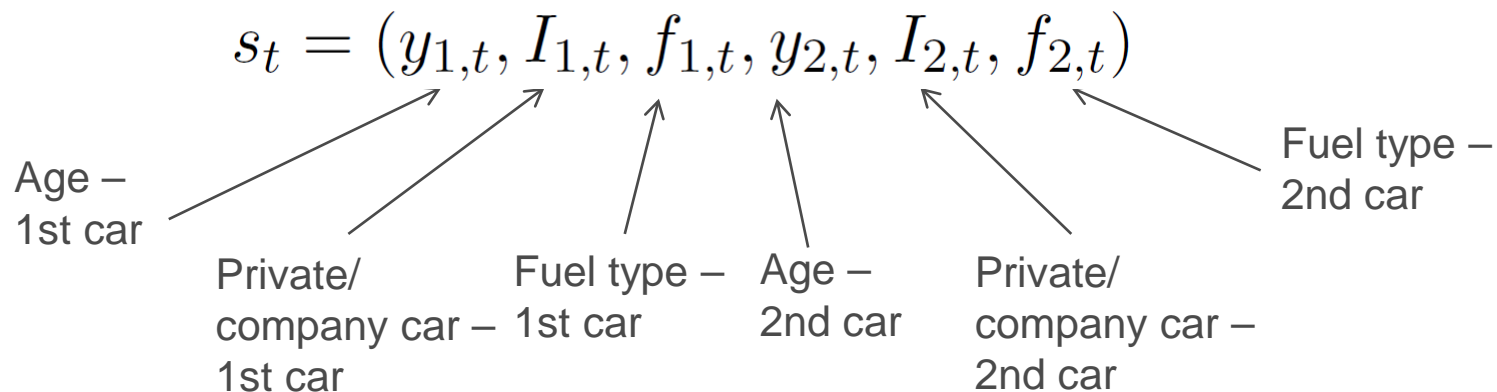
- **Agent:** household
- **Time step** t : year
- **State space** S



$$\begin{aligned}
 |S| &= (|Y| \times (|I_C| - 2) \times (|F| - 1) + 1)^2 \\
 &+ (|Y| \times (|I_C| - 2) \times (|F| - 1) + 1) \\
 &+ 1.
 \end{aligned}$$

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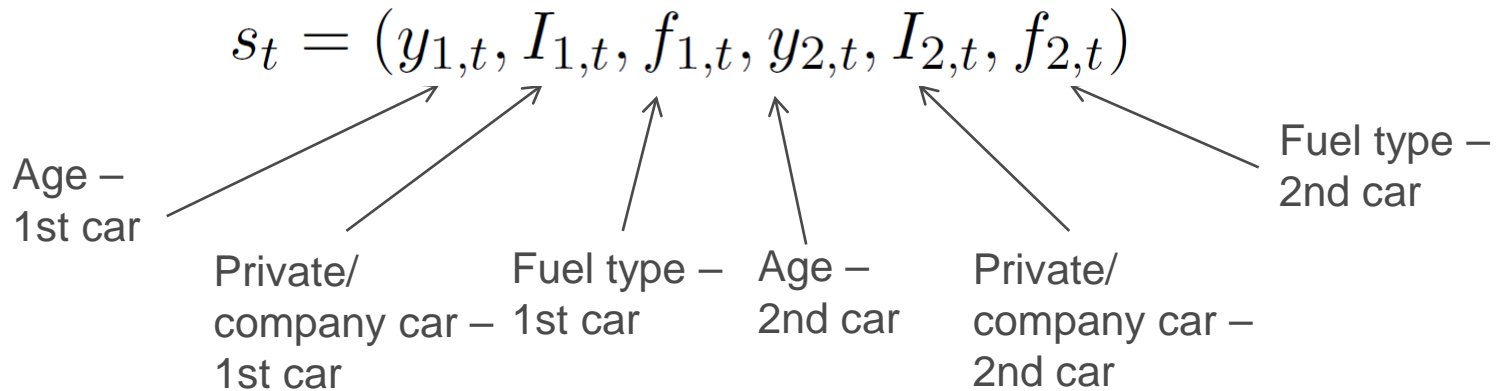
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$$\begin{aligned}
 |S| &= \boxed{(|Y| \times (|I_C| - 2) \times (|F| - 1) + 1)^2} \text{ 2-car households} \\
 &+ (|Y| \times (|I_C| - 2) \times (|F| - 1) + 1) \\
 &+ 1.
 \end{aligned}$$

Definition of the components of the dynamic programming model:

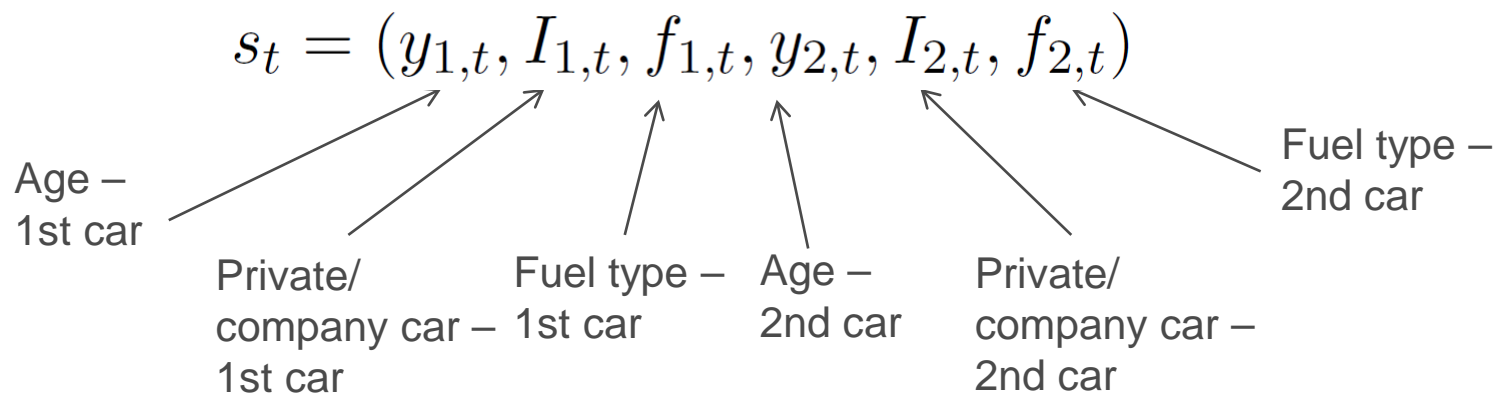
- **Agent:** household
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- **State space** S



$$\begin{aligned}
 |S| &= (|Y| \times (|I_C| - 2) \times (|F| - 1) + 1)^2 \\
 &+ \boxed{(|Y| \times (|I_C| - 2) \times (|F| - 1) + 1)} \text{ 1-car households} \\
 &+ 1.
 \end{aligned}$$

Definition of the components of the dynamic programming model:

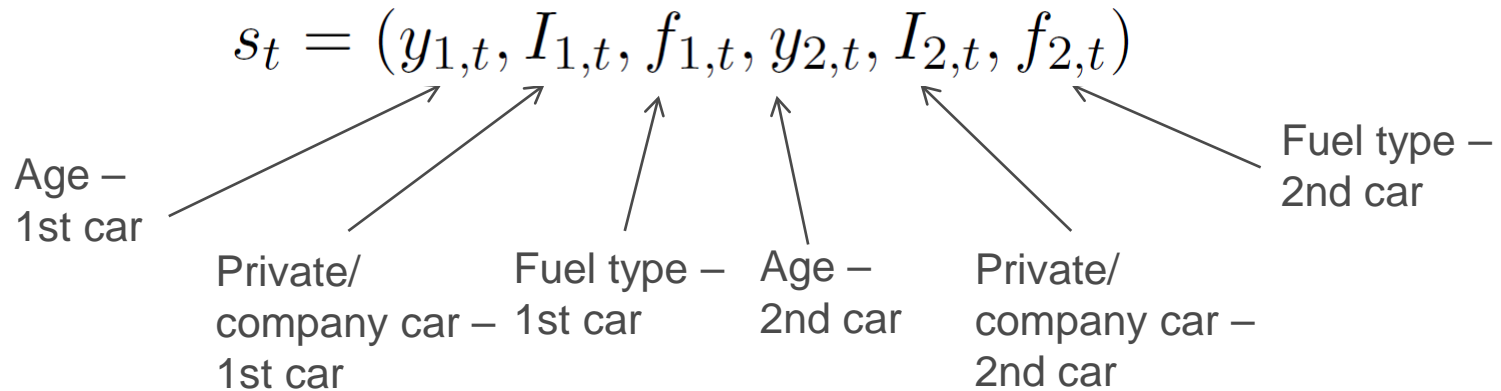
- **Agent:** household
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$$\begin{aligned}
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 &+ (|Y| \times (|I_C| - 2) \times (|F| - 1) + 1) \\
 &+ \boxed{1}. \text{ 0-car households}
 \end{aligned}$$

Definition of the components of the dynamic programming model:

- **Agent:** household
- **Time step** t : year
- **State space** S



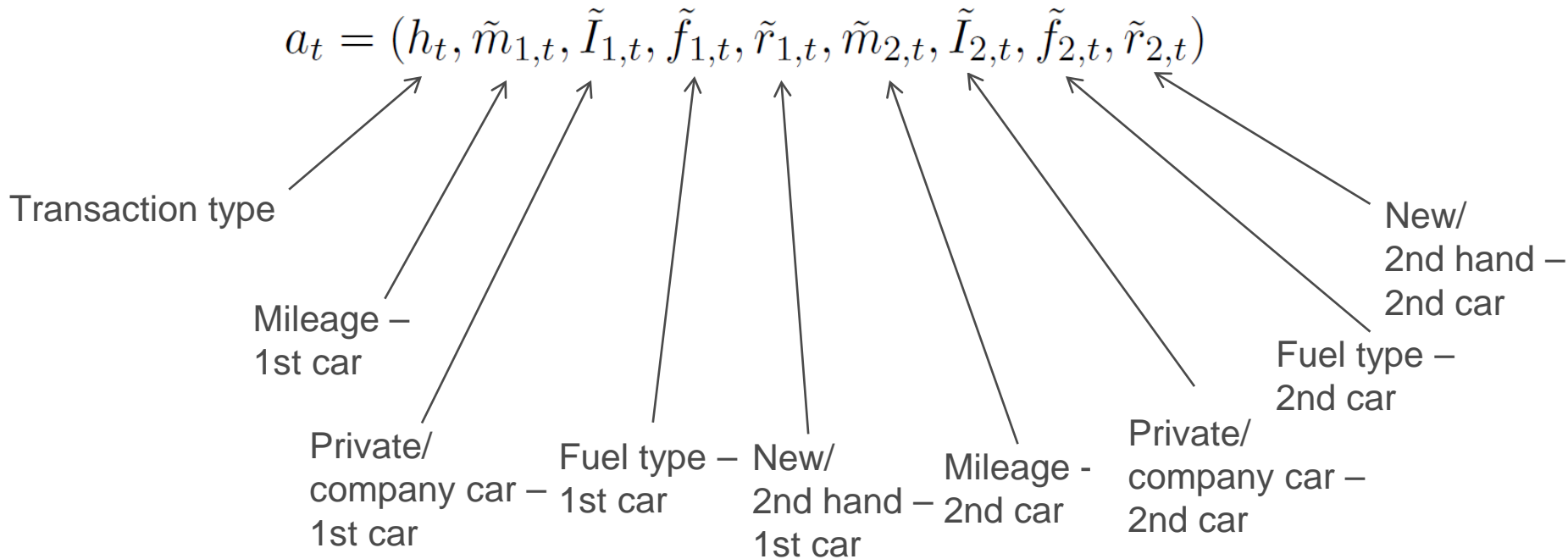
$$|S| = (|Y| \times (|I_C| - 2) \times (|F| - 1) + 1)^2$$

$$+ (|Y| \times (|I_C| - 2) \times (|F| - 1) + 1)$$

$$+ 1. = 1407 \rightarrow \text{relatively small state space}$$

Definition of the components of the dynamic programming model:

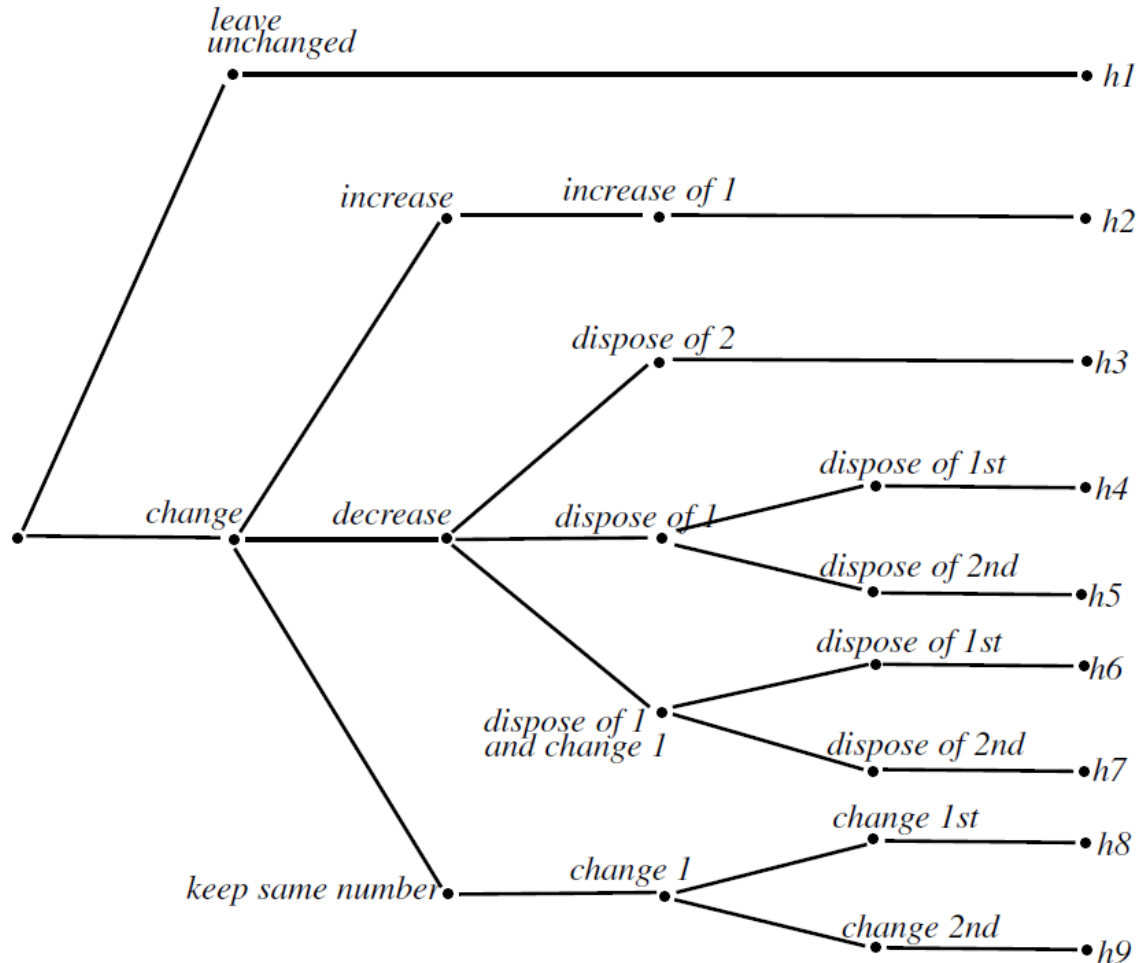
- **Action space** A



Definition of the components of the dynamic programming model:

- **Action space** A

Transaction type: details



Definition of the components of the dynamic programming model:

- **Action space A**

Transaction name	0 car	1 car	2 cars
$h1$: leave unchanged	1	4	16
$h2$: increase 1	72	288	-
$h3$: dispose 2	-	-	1
$h4$: dispose 1st	-	1	4
$h5$: dispose 2nd	-	-	4
$h6$: dispose 1st and change 2nd	-	-	72
$h7$: dispose 2nd and change 1st	-	-	72
$h8$: change 1st	-	72	288
$h9$: change 2nd	-	-	288
Sum	73	365	745

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Size of the action space assuming:

- 4 levels mileage
- 3 levels company car
- 3 levels fuel type
- 2 levels new/2nd hand

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Size of the action space assuming:

- 4 levels mileage
- 3 levels company car
- 3 levels fuel type
- 2 levels new/2nd hand

Maximum size of action space

Definition of the components of the dynamic programming model:

- **Instantaneous utility:** $u(s_t, a_t, x_t, \theta) = v(s_t, a_t, x_t, \theta) + \varepsilon(a_t)$
- **Transition rule:** deterministic rule: each state s_{t+1} can be inferred exactly once s_t and a_t are known.

Example:

If $s_t = [2, 1, 2, 0, 0, 0]$ and $a_t = [1, 2, 0, 0, 0, 1, 3, 0, 0]$

then $s_{t+1} = [3, 1, 2, 0, 3, 0]$.

Annotations for s_t and a_t :

- 2 ans (points to the first element of s_t)
- private car (points to the second element of s_t)
- diesel (points to the third element of s_t)
- increase 1 (points to the first element of a_t)
- mileage level 1 (points to the sixth element of a_t)
- mileage level 2 (points to the seventh element of a_t)
- company car (points to the eighth element of a_t)

Resolution of the dynamic programming problem:

Value iteration

- Value function:

$$V(s_t, x_t, \theta) = \max_{a_t \in A} \{u(s_t, a_t, x_t, \theta) + \beta \sum_{s_{t+1} \in S} \bar{V}(s_{t+1}, x_{t+1}, \theta) f(s_{t+1} | s_t, a_t)\}$$

- Using the integrated value function $\bar{V}(s_t, x_t, \theta) = \int V(s_t, x_t, \varepsilon_t) dG_\varepsilon(\varepsilon_t)$
 - Another update rule that has a closed-form expression can be defined
 - Obtained from the expected maximum utility

$$\bar{V}(s_t, x_t, \theta) = \log \sum_{a_t \in A} \exp\{v(s_t, a_t, x_t, \theta) + \beta \sum_{s_{t+1} \in S} \bar{V}(s_{t+1}, x_{t+1}, \theta) f(s_{t+1} | s_t, a_t)\}$$

Resolution of the DDCM problem:

- Parameters obtained by maximizing likelihood:

$$\mathcal{L} = \prod_{n=1}^N \prod_{t=1}^T P(a_{n,t} | s_{n,t}, x_{n,t}, \theta) f(s_{n,t} | s_{n,t-1}, a_{n,t-1})$$

- Optimization algorithm is Rust's **nested fixed point algorithm** (Rust, 1987):
 - **Outer optimization algorithm:** search algorithm to obtain parameters maximizing likelihood
 - **Inner value iteration algorithm:** solves the DP problem for each parameter trial

Preliminary results for the value iteration algorithm:

Inputs:

- **Size state space = 1407**
 - Max age = 5
 - Company car levels = 3
 - Number of fuel types = 3
- **Size action space = max 745**
 - Number of transaction types = 9
 - Number of mileage levels = 4
 - Number of levels of new/old = 2
- **Utility function contains:**
 - Transaction-dependent parameters for fuel type
 - Transaction-dependent parameters for age of oldest car } arbitrarily defined
- **Parameters of DP problem:**
 - Discount factor $\beta = 0.7$
 - Stopping criterion $\varepsilon = 0.01$

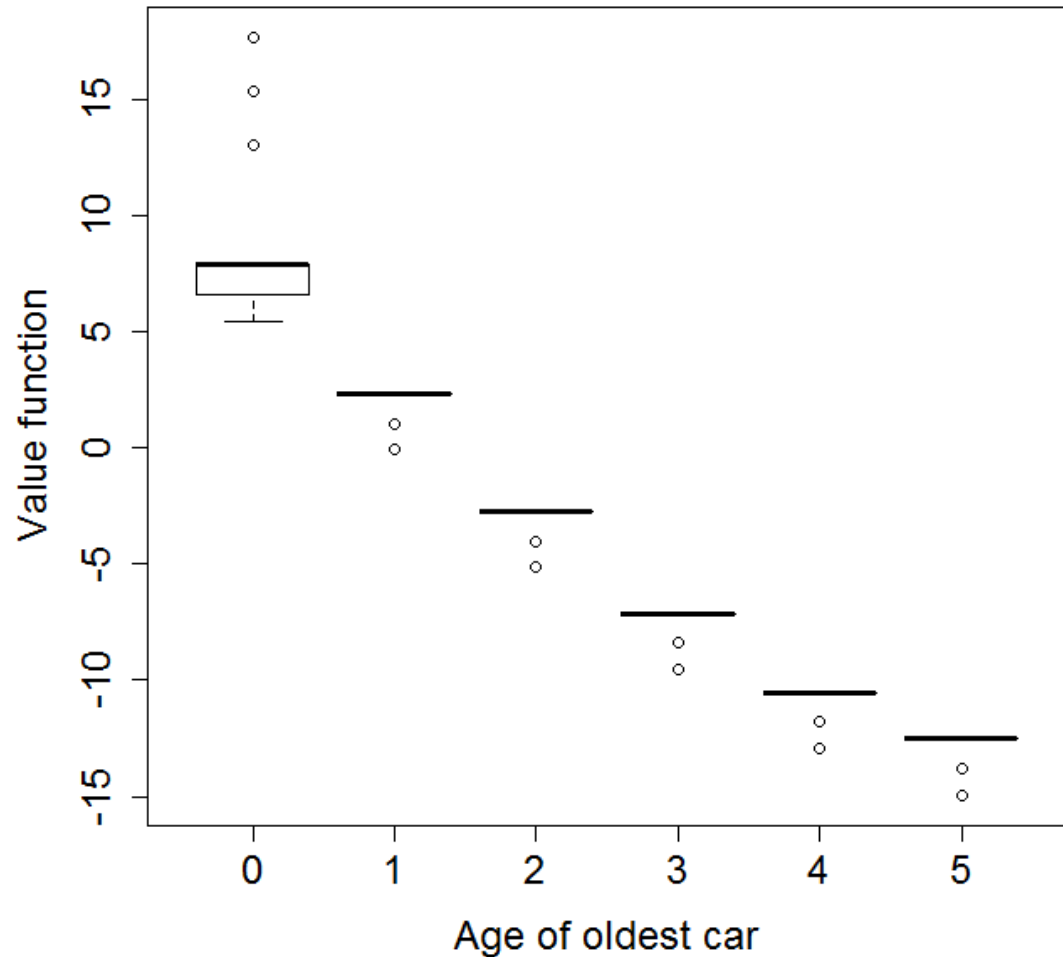
Preliminary results for the value iteration algorithm:

Program:

- Prototype in Matlab
- 15 hours on 8-core server

Graph:

- \bar{V} vs age of oldest of 2 cars



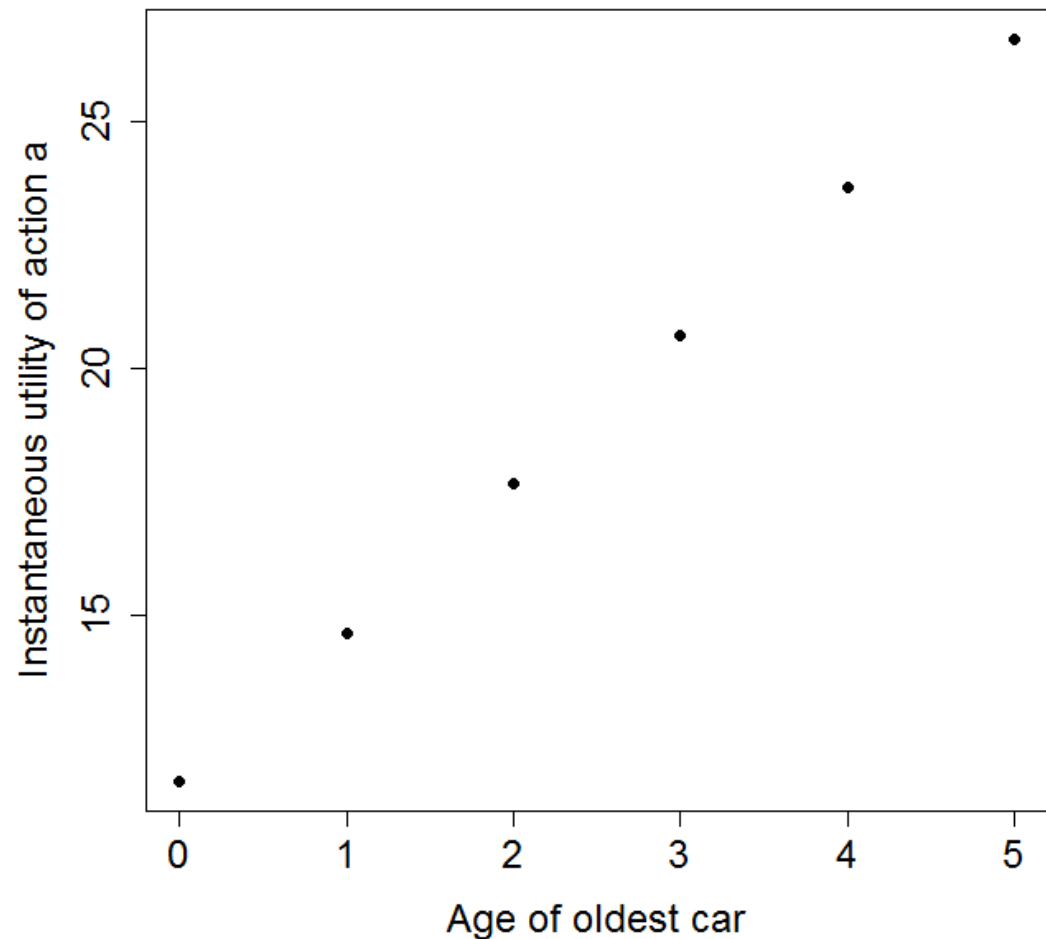
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Graph:

- Assume an initial action $a = [3, 1, 0, 0, 0, 0, 0, 0, 0]$
 $u(a)$ vs age of oldest car



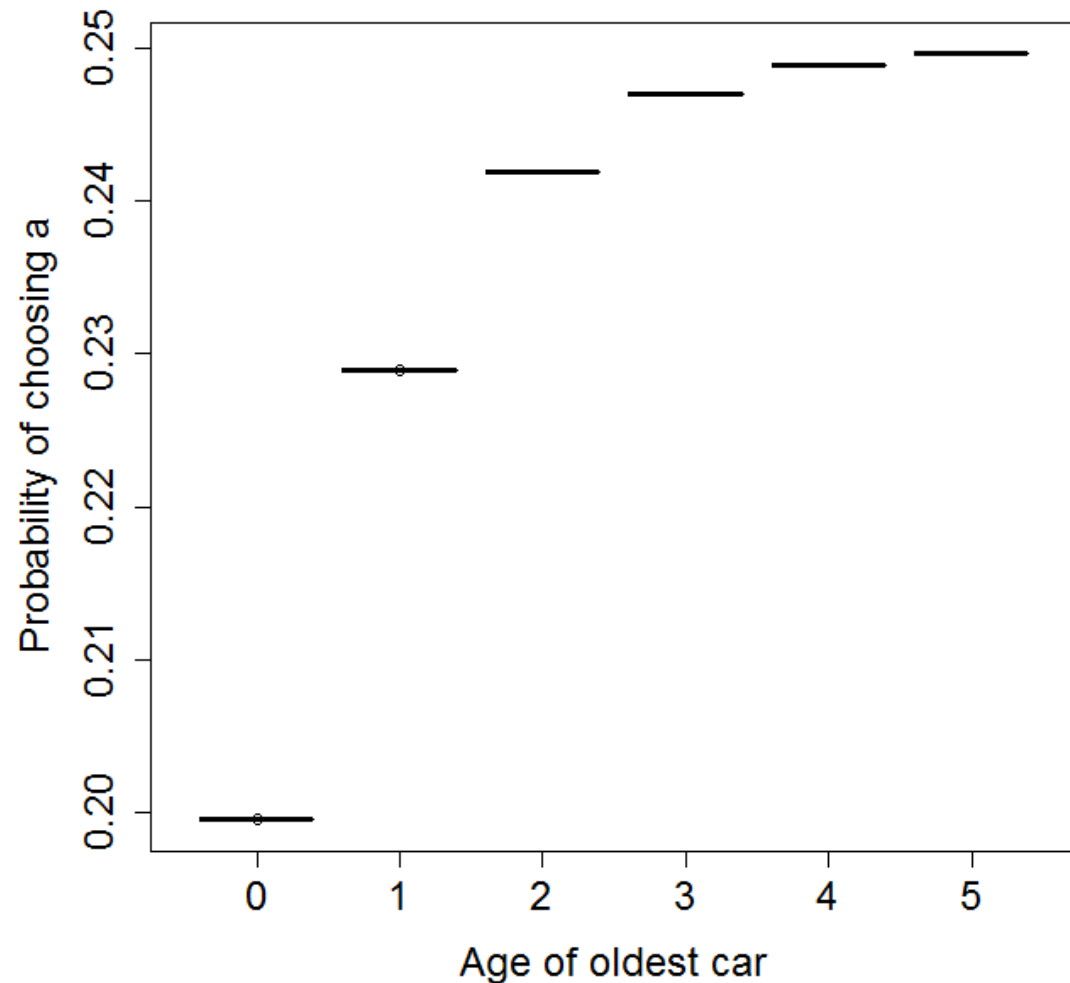
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Graph:

- Assume an initial action $a = [3, 1, 0, 0, 0, 0, 0, 0, 0]$
 $P(a)$ vs age of oldest car



Conclusion:

- First results of value function
- Shows feasibility of problem

Future works:

- Speed up computation of integrated value function \Rightarrow C++
- Sequential choice of two vehicles if computational time still too large
- Exploratory analysis to specify instantaneous utility
- Implement outer loop (maximization algorithm)
- Scenario testing:
 - Validation of policy measures taken during the years available in the data
 - Test policy measures that are planned to be applied in future years

Thanks!

