

IDENTIFICATION OF MIXTURES OF DYNAMIC DISCRETE CHOICES

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This version: June 14, 2022

Abstract

This paper provides new identification results for finite mixtures of Markov processes. Our arguments yield identification from knowledge of the cross-sectional distribution of three (or more) effective time-series observations under simple conditions. Our approach is contrasted with the ones taken by [Kasahara and Shimotsu \(2009\)](#) and [Hu and Shum \(2012\)](#). Notably, outside information, such as monotonicity restrictions that link conditional distributions to latent types, is not needed. Maximum likelihood is considered for the purpose of estimation and inference. Implementation via the EM algorithm is straightforward. The performance of this procedure is evaluated in a simulation exercise.

JEL Classification: C14, C23 C51

Keywords: discrete choice, heterogeneity, Markov process, mixture, state dependence

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Support from the European Research Council through grant n° 715787 (MiMo), and from the French Government and the ANR under the Investissements d'Avenir program, grant ANR-17-EURE-0010 is gratefully acknowledged. Thierry Magnac and seminar participants at Brown, HKUST, and Yale gave much appreciated feedback.

Introduction

The analysis of dynamic discrete choices from short panel data is fundamental in applied work. Allowing for unobserved heterogeneity in such a setting is recognized to be important ([Heckman 1981](#)) but doing so in a flexible manner is known to be difficult. A leading paradigm is to presume that the population of agents is composed of a finite number of (latent) types, implying that the (marginal) distribution of the data takes the form of a finite mixture. [Keane and Wolpin \(1997\)](#), [Eckstein and Wolpin \(1999\)](#), [Crawford and Schum \(2005\)](#), [Wang \(2014\)](#), [Nevo, Turner and Williams \(2016\)](#), and [Rossi \(2017\)](#) are examples of papers that have taken this route.

[Kasahara and Shimotsu \(2009\)](#) have studied the (nonparametric) identifiability of finite mixtures of first-order Markov processes. Their work is commonly invoked in the literature to claim identification; see, e.g., [Arcidiacono and Miller \(2011\)](#), [Baum-Snow and Pavan \(2012\)](#), [Norets and Tang \(2014\)](#), [Chen \(2017\)](#), [Kalouptsi, Scott and Souza-Rodrigues \(2020\)](#), [Kalouptsi, Kitamura, Lima and Souza-Rodrigues \(2021\)](#). The approach taken in [Kasahara and Shimotsu \(2009\)](#) closely follows work on (static) multivariate models with latent variables (in particular [Anderson 1954](#) and [Hall and Zhou 2003](#)). Moreover, they exploit implications of the dynamic model to which the machinery for identification in the static case can be applied. These restrictions are, however, not sufficient to recover the type-specific distributions or the mixing distribution. This issue does not seem to be well appreciated and is a subtle consequence of the fact that the labelling of types is arbitrary, and can be changed without observable implications. We discuss this in more detail below. [Hu and Shum \(2012\)](#) follow a similar strategy to [Kasahara and Shimotsu \(2009\)](#), relying on restrictions inspired by the approach of [Hu \(2008\)](#). These restrictions again do not suffice to obtain identification. To resolve the issue, [Hu and Shum \(2012\)](#) supplement the model with outside information in the form of a set of monotonicity restrictions that link latent types to observable choices. Aside from practical issues that arise when taking such an approach to the data, monotonicity conditions may be difficult to come up with or may simply not be available in many applications. As such, this type of solution leaves something to be

desired.

We develop a new identification argument that shows that the type-specific transition kernels, the type-specific distributions of the initial condition, and the mixing distribution are all recoverable from knowledge of the cross-sectional distribution of as little as four time-series observations under three simple conditions which ensure that the type-specific Markov processes are sufficiently different. Like [Kasahara and Shimotsu \(2009\)](#) and [Hu and Shum \(2012\)](#), we, too, exploit (different) multilinear restrictions that are reminiscent of those employed in the literature on multivariate mixtures. However, these are only a subset of a larger set of restrictions implied by the Markovian structure of the model. While the subset of restrictions alone does not fully identify the unknown distributions, the full set of restrictions does. Identification is achieved without the need to impose additional structure, such as monotonicity restrictions. Our arguments also extend naturally to models with higher-order Markovian dependence. The general conclusion, then, is that mixtures of p -th order Markov processes can be identified from the cross-sectional distribution of $3 + p$ time-series observations.

The model is introduced in Section 1. Our assumptions and identification argument are presented in Section 2. A detailed comparison with the assumptions and approaches of [Kasahara and Shimotsu \(2009\)](#) and [Hu and Shum \(2012\)](#) is made in Section 3. Maximum likelihood can be used for estimation and inference and we discuss this in Section 4. As usual with mixture models, the EM algorithm is attractive for implementation. Furthermore, in the current setting, both the E-step as the M-step are available in closed form. We show how our approach extends to models with higher-order Markovian dependence in Section 5.

1 Mixtures of dynamic discrete choices

Suppose that Z is a latent random variable that can take on q values, where q is a known integer. We normalize its support to the set of integers up to q , which is without loss of generality, and write μ_1, \dots, μ_q for its probability mass function. So, $\mu_z := \mathbb{P}(Z = z) > 0$

for $1 \leq z \leq q$ and zero otherwise. Next let $\{X_t\}$ be a sequence of observable random variables that can take on r values. We presume that its support constitutes the set of integers up to r . This is merely for notational convenience in what is to follow; translation of the support to a general set is straightforward. Conditional on $Z = z$, the sequence $\{X_t\}$ follows a first-order Markov process. The process is initialized with a draw from the distribution

$$s_z(x) := \mathbb{P}(X_1 = x | Z = z),$$

and subsequently evolves according to the time-homogeneous transition kernel

$$k_z(x, x') := \mathbb{P}(X_t = x' | X_{t-1} = x, Z = z).$$

This delivers a dynamic model of discrete choice with unobserved heterogeneity captured by a mixture over q latent types. The dynamic processes are allowed to be non-stationary in that the initial conditions are not assumed to have been drawn from the steady-state distribution.

Our goal is to nonparametrically recover the distribution of the latent types, μ_1, \dots, μ_q , the distributions of the initial conditions, s_1, \dots, s_q , and the transition kernels, k_1, \dots, k_q , from knowledge of the joint distribution of X_1, X_2, X_3, X_4 . Our arguments to follow can be generalized to the case where additional time-series observations are available and we discuss how to do so below. As latent types can be relabelled without any observable implications, identification here is to be understood as being up to an arbitrary re-ordering of types.

Before turning to the identification analysis it is useful to point out that restricting attention to univariate variables is without loss of generality. To see this, suppose that we are interested in a sequence of p -dimensional vectors \mathbf{Y}_t whose entries can take on, respectively, r_1, \dots, r_p values. Then we can always enumerate all values in the state space of \mathbf{Y}_t and define a scalar random variable X_t on this set of numbers that is a (known) one-to-one transformation of \mathbf{Y}_t . This random variable can take on $r = r_1 \times \dots \times r_p$ values. Identification of a mixture on X_t then implies identification of the corresponding mixture on \mathbf{Y}_t . As will become apparent below, a larger r can only make the identification

problem easier, and so observing more variables is helpful for identification. This connects to the discussion in [Hall and Zhou \(2003\)](#) and [Hall, Neeman, Pakyari and Elmore \(2005\)](#) on the identification power of multivariate mixtures. It might be the case that, for a partition $\mathbf{Y}_t = (\mathbf{Y}_{t,1}, \mathbf{Y}_{t,2})$, the ultimate goal is to recover the (type-specific) distribution of the initial condition and the transition kernel of $\mathbf{Y}_{t,1}$ conditional on $\mathbf{Y}_{t,2}$. Here, $\mathbf{Y}_{t,1}$ is the outcome of interest while $\mathbf{Y}_{t,2}$ plays the role of covariates. This is often the case in structural models of dynamic discrete choice and corresponds to the point of view in [Kasahara and Shimotsu \(2009\)](#). Such conditional distributions are, of course, identified once the joint distribution is.

2 Identification

Assumptions. Our constructive identification approach employs three assumptions. We first introduce notation for probabilities that involve only observable variables. We will use the shorthands $p_{x_1, x_2} := \mathbb{P}(X_1 = x_1, X_2 = x_2)$ and $p_{x_1, x_2, x_3} := \mathbb{P}(X_1 = x_1, X_2 = x_2, X_3 = x_3)$ as well as $p_{x_1, x_2, x_3, x_4} := \mathbb{P}(X_1 = x_1, X_2 = x_2, X_3 = x_3, X_4 = x_4)$. First, we collect all the bivariate probabilities into the two sets of r -vectors $\mathbf{p}_1, \dots, \mathbf{p}_r$ and $\mathbf{p}_1^*, \dots, \mathbf{p}_r^*$, where we write

$$\mathbf{p}_x := (p_{1,x}, \dots, p_{r,x})^\top, \quad \mathbf{p}_x^* := (p_{x,1}, \dots, p_{x,r})^\top.$$

Note that $\mathbf{p}_x \neq \mathbf{p}_x^*$, in general. Similarly, we construct $r \times r$ matrices $\mathbf{P}_1, \dots, \mathbf{P}_r$ containing trivariate probabilities, letting

$$(\mathbf{P}_x)_{i,j} := p_{j,x,i}.$$

Finally, we do the same for probabilities involving all four periods, by introducing the $r \times r$ matrices

$$(\mathbf{P}_{x,x'})_{i,j} := p_{j,x,x',i},$$

with (x, x') ranging over all the r^2 possibilities. The probabilities involved here are all nonparametrically identified and these matrices may thus all be considered known for our purposes.

Our first assumption is a rank condition that is directly testable from the data.

Assumption 1. *For each x the $r \times r$ matrix \mathbf{P}_x has rank q .*

A necessary condition for this assumption to hold is that $r \geq q$. The decomposition in Equation (2.1) below shows that Assumption 1 implies that, for each x , the conditional distributions of X_t given $X_{t-1} = x$ and $Z = z$ (seen as a function of z) are linearly independent. The need for this is intuitive. On the other hand, the rank condition allows for the presence of, for example, absorbant states, i.e., that, for some x and z , $k_z(x, x) = 1$, and so $k_z(x, x') = 0$ for all $x' \neq x$. It also does not require that state dependence necessarily be present in order to go through. Indeed, we may have that $k_z(x', x) = k_z(x'', x)$ for all pairs (x', x'') and for all x .

To state our second assumption we let

$$f_{z,x,m}(x_1, \dots, x_m) := k_z(x, x_1) \left(\bigotimes_{i=2}^m k_z(x_{i-1}, x_i) \right) k_z(x_m, x),$$

which is the probability of arriving in State x via the walk x_1, \dots, x_m when starting at State x itself, conditional on $Z = z$. Stack the probabilities over the different possible walks x_1, \dots, x_m in the vector $\mathbf{f}_{z,x,m}$ and collect these distributions over latent types in the matrix $\mathbf{F}_{x,m} := (\mathbf{f}_{1,x,m}, \dots, \mathbf{f}_{q,x,m})$.

Assumption 2. *For each x there exists an integer o such that the columns of the matrix*

$$\mathbf{F}_x := (\mathbf{F}_{x,m_1}^\top, \dots, \mathbf{F}_{x,m_o}^\top)^\top$$

are all distinct.

This requirement is quite weak. A simple sufficient condition for Assumption 2 is that there exists an m for which the distributions $\mathbf{f}_{z,x,m}$ and $\mathbf{f}_{z',x,m}$ are different for all pairs (z, z') . That is, for each x , there exists at least one walk from x going back to x that occurs with a different probability for each type.

Our third and last assumption reads as follows.

Assumption 3. *There exists a value x_0 and a finite sequence x_1, \dots, x_m for which either*

$$(i) \ k_z(x_0, x_1) \left(\bigotimes_{i=2}^m k_z(x_{i-1}, x_i) \right) k_z(x_m, x) \quad \text{or} \quad (ii) \ k_z(x, x_1) \left(\bigotimes_{i=2}^m k_z(x_{i-1}, x_i) \right) k_z(x_m, x_0)$$

is non-zero for each z and for all $x \neq x_0$.

Assumption 3 requires that there exists a walk that connects the value x_0 to all other values x for all types, either going from x_0 to x , or from x to x_0 . The developments to follow will make it apparent that evaluating whether any particular sequence of values satisfies this assumption can be done by testing whether a collection of $q \times q$ matrices have maximal rank.

Identification. We begin by constructing, for each x , the $r \times q$ matrices \mathbf{K}_x and \mathbf{L}_x as

$$(\mathbf{K}_x)_{x',z} := k_z(x, x'), \quad (\mathbf{L}_x)_{x',z} := \mu_z s_z(x') k_z(x', x).$$

Next, we appeal to the Markovian structure of our model to see that, for each x , the factorization

$$\mathbf{P}_x = \mathbf{K}_x \mathbf{L}_x^\top \tag{2.1}$$

holds. Assumption 1 states that each $r \times r$ matrix \mathbf{P}_x has rank equal to q . Hence, it has the singular-value decomposition

$$\mathbf{P}_x = \mathbf{U}_x \mathbf{E}_x \mathbf{V}_x^\top,$$

for unitary $r \times q$ matrices of, respectively, left and right singular vectors, \mathbf{U}_x and \mathbf{V}_x , and $q \times q$ diagonal matrices \mathbf{E}_x of singular values. It then follows that, if we use the shorthands $\mathbf{A}_x := \mathbf{E}_x^{-1/2} \mathbf{U}_x^\top$ and $\mathbf{B}_x := \mathbf{E}_x^{-1/2} \mathbf{V}_x^\top$,

$$\mathbf{A}_x \mathbf{P}_x \mathbf{B}_x^\top = \mathbf{I}_q, \tag{2.2}$$

with \mathbf{I}_q being the $q \times q$ identity matrix. Now introduce the $q \times q$ matrix $\mathbf{Q}_x := \mathbf{A}_x \mathbf{K}_x$. Combining Equation (2.1) with Equation (2.2) reveals that

$$\mathbf{I}_q = \mathbf{A}_x \mathbf{P}_x \mathbf{B}_x^\top = (\mathbf{A}_x \mathbf{K}_x) (\mathbf{B}_x \mathbf{L}_x)^\top = \mathbf{Q}_x \mathbf{Q}_x^{-1},$$

and so $\mathbf{Q}_x^{-\top} = \mathbf{B}_x \mathbf{L}_x$ must hold.

We now turn to the distribution of all four observable variables. Notice that, in the same way as before,

$$\mathbf{P}_{x,x'} = \mathbf{K}_{x'} \mathbf{D}_{x,x'} \mathbf{L}_x^\top,$$

where $\mathbf{D}_{x,x'} := \text{diag}(k_1(x, x'), \dots, k_q(x, x'))$ collects the transition probabilities from state x to x' for each of the different types z . Hence,

$$\mathbf{C}_{x,x'} := \mathbf{A}_{x'} \mathbf{P}_{x,x'} \mathbf{B}_x^\top = \mathbf{Q}_{x'} \mathbf{D}_{x,x'} \mathbf{Q}_x^{-1} \quad (2.3)$$

for all (x, x') .

A first implication of Equation (2.3) is that, for each x and all x' ,

$$\mathbf{C}_{x',x} \mathbf{C}_{x,x'} = (\mathbf{Q}_x \mathbf{D}_{x',x} \mathbf{Q}_{x'}^{-1}) (\mathbf{Q}_{x'} \mathbf{D}_{x,x'} \mathbf{Q}_x^{-1}) = \mathbf{Q}_x (\mathbf{D}_{x,x'} \mathbf{D}_{x',x}) \mathbf{Q}_x^{-1}$$

and, more generally, that, for each x and for any sequence of m values x_1, \dots, x_m ,

$$\mathbf{C}_{x_m,x} \mathbf{C}_{x_{m-1},x_m} \cdots \mathbf{C}_{x_1,x_2} \mathbf{C}_{x,x_1} = \mathbf{Q}_x (\mathbf{D}_{x,x_1} \mathbf{D}_{x_1,x_2} \cdots \mathbf{D}_{x_{m-1},x_m} \mathbf{D}_{x_m,x}) \mathbf{Q}_x^{-1}.$$

That is, \mathbf{Q}_x is a joint diagonalizer of a set of matrices. Notice that the z -th diagonal entry of $\mathbf{D}_{x,x_1} \mathbf{D}_{x_1,x_2} \cdots \mathbf{D}_{x_{m-1},x_m} \mathbf{D}_{x_m,x}$ is $f_{z,x,m}(x_1, \dots, x_m)$. Moreover, the eigenvalues of the set of matrices $\mathbf{C}_{x_m,x} \mathbf{C}_{x_{m-1},x_m} \cdots \mathbf{C}_{x_1,x_2} \mathbf{C}_{x,x_1}$ (as a function of x_1, \dots, x_m) are the rows of the matrix $\mathbf{F}_{x,m}$. Further, because the joint diagonalizer is independent of m , the same \mathbf{Q}_x equally diagonalizes the matrices $\mathbf{C}_{x'_m,x} \mathbf{C}_{x'_{m-1},x'_m} \cdots \mathbf{C}_{x'_1,x'_2} \mathbf{C}_{x,x'_1}$ (as a function of x'_1, \dots, x'_m) for any different walk length m' . Take a set of o such walk lengths, m_1, \dots, m_o . This delivers a joint diagonalization problem whose eigenvalues are the rows of the matrix \mathbf{F}_x . By Assumption 2 there exists an o for which the columns of \mathbf{F}_x are all distinct. It then follows from Theorem 6.1 of De Lathauwer, De Moor and Vandewalle (2004) that the matrix \mathbf{Q}_x is unique up to the scale and ordering of its columns. That is, a joint diagonalization problem identifies the matrix $\tilde{\mathbf{Q}}_x := \mathbf{Q}_x \mathbf{\Omega}_x \mathbf{\Delta}_x$, where $\mathbf{\Omega}_x$ is a diagonal scaling matrix and $\mathbf{\Delta}_x$ is a permutation matrix.

The diagonal matrix $\mathbf{\Omega}_x$ can be recovered, up to permutation of the entries on its diagonal, from the observation that

$$\mathbf{u}_x := \mathbf{B}_x \mathbf{p}_x = \mathbf{B}_x \mathbf{L}_x \boldsymbol{\iota}_q = \mathbf{Q}_x^{-\top} \boldsymbol{\iota}_q,$$

where the first transition uses the model structure, the second follows from the definition of \mathbf{Q}_x , and $\mathbf{1}_q$ denotes the q -vector of ones. Moreover,

$$\tilde{\mathbf{Q}}_x^\top \mathbf{u}_x = \Delta_x^{-1} \Omega_x \mathbf{1}_q = \Delta_x^{-1} \Omega_x \Delta_x \mathbf{1}_q,$$

using that each row of any permutation matrix sums to unity. It is easy to see that the matrix $\Delta_x^{-1} \Omega_x \Delta_x$ on the right-hand side is diagonal; a proof is provided in Lemma A.1 in the Appendix. We, therefore, indeed recover

$$\tilde{\Omega}_x := \Delta_x^{-1} \Omega_x \Delta_x$$

for all x .

Moving on, let the value x_0 and the sequence x_1, \dots, x_m be such that Condition (i) in Assumption 3 is satisfied; working with Condition (ii) is analogous and, therefore, not dealt with further. Using the same argument as before it is easy to see that a second implication of Equation (2.3) is that

$$\tilde{\mathbf{D}}_{x_0,x} := \tilde{\mathbf{Q}}_x^{-1} (\mathbf{C}_{x_m,x} \mathbf{C}_{x_{m-1},x_m} \cdots \mathbf{C}_{x_0,x_1}) \tilde{\mathbf{Q}}_{x_0} = \Delta_x^{-1} \dot{\mathbf{D}}_{x_0,x} \Delta_{x_0},$$

where the matrices $\dot{\mathbf{D}}_{x_0,x} := \Omega_{x_0} (\mathbf{D}_{x_0,x_1} \mathbf{D}_{x_1,x_2} \cdots \mathbf{D}_{x_m,x}) \Omega_x^{-1}$ are diagonal. We can write

$$\tilde{\mathbf{D}}_{x_0,x} = \Delta_x^{-1} \dot{\mathbf{D}}_{x_0,x} \Delta_{x_0} = \Delta_x^{-1} \Delta_{x_0} (\Delta_{x_0}^{-1} \dot{\mathbf{D}}_{x_0,x} \Delta_{x_0}). \quad (2.4)$$

Note that the matrix $\Delta_x^{-1} \Delta_{x_0}$ is a product of permutation matrices and, hence, is itself a permutation matrix. Therefore, $\tilde{\mathbf{D}}_{x_0,x}$ is equal to $\Delta_{x_0}^{-1} \dot{\mathbf{D}}_{x_0,x} \Delta_{x_0}$ up to ordering of the rows. The latter matrix is diagonal. The diagonal entries of $\Delta_{x_0}^{-1} \dot{\mathbf{D}}_{x_0,x} \Delta_{x_0}$ are thus identified by the column sums of the matrix $\tilde{\mathbf{D}}_{x_0,x}$. From Equation (2.4), coupled with Assumption 3, it follows that

$$\mathbf{H}_{x,x_0} := \Delta_x^{-1} \Delta_{x_0} = \tilde{\mathbf{D}}_{x_0,x} (\Delta_{x_0}^{-1} \dot{\mathbf{D}}_{x_0,x} \Delta_{x_0})^{-1}$$

is identified for all x . With these matrices in hand we may re-arrange the diagonal entries of the scaling matrices in a common order, as

$$\mathbf{H}_{x,x_0}^{-1} \tilde{\Omega}_x \mathbf{H}_{x,x_0} = \Delta_{x_0}^{-1} \Omega_x \Delta_{x_0} =: \bar{\Omega}_x,$$

and subsequently recover

$$\bar{\mathbf{Q}}_x := \tilde{\mathbf{Q}}_x \mathbf{H}_{x,x_0} \bar{\Omega}_x^{-1} = \mathbf{Q}_x \Delta_{x_0}$$

for all x . Thus, we have identified the matrices of joint eigenvectors $\mathbf{Q}_1, \dots, \mathbf{Q}_r$ up to a common permutation of their columns. We can now recover the parameters of our mixture model, up to the permutation Δ_{x_0} .

First, from Equation (2.3) we can directly recover the transition kernels, as

$$\bar{\mathbf{Q}}_{x'}^{-1} \mathbf{C}_{x,x'} \bar{\mathbf{Q}}_x = \Delta_{x_0}^{-1} \mathbf{D}_{x,x'} \Delta_{x_0} =: \bar{\mathbf{D}}_{x,x'}.$$

Because the diagonal of $\mathbf{D}_{x,x'}$ constitutes the x' -th row of matrix \mathbf{K}_x , knowledge of $\bar{\mathbf{D}}_{x,x'}$ for all (x, x') allows us to construct the matrix $\bar{\mathbf{K}}_x := \mathbf{K}_x \Delta_{x_0}$ for each x . Next, the Markov structure of the model implies that

$$\mathbf{p}_x^* = \mathbf{K}_x \boldsymbol{\lambda}_x,$$

where $\boldsymbol{\lambda}_x := (s_1(x) \mu_1, \dots, s_q(x) \mu_q)^\top$. By consequence of Assumption 1, each \mathbf{K}_x has maximal column rank. Letting a $+$ superscript on a matrix indicate its left inverse, we may thus calculate

$$\bar{\mathbf{K}}_x^+ \mathbf{p}_x^* = \Delta_{x_0}^{-1} \mathbf{K}_x^+ \mathbf{p}_x^* = \Delta_{x_0}^{-1} \boldsymbol{\lambda}_x =: \bar{\boldsymbol{\lambda}}_x,$$

for each x . Collecting $\bar{\boldsymbol{\Lambda}} := (\bar{\boldsymbol{\lambda}}_1, \dots, \bar{\boldsymbol{\lambda}}_r)^\top$ yields the joint distribution of types and initial conditions. Indeed, with $\boldsymbol{\Lambda} := (\boldsymbol{\lambda}_1, \dots, \boldsymbol{\lambda}_r)^\top$, we see that $\bar{\boldsymbol{\Lambda}} = \boldsymbol{\Lambda} \Delta_{x_0}$. Finally, letting $\boldsymbol{\mu} := (\mu_1, \dots, \mu_q)^\top$ and $\mathbf{S} := (\mathbf{s}_1, \dots, \mathbf{s}_q)$, where $\mathbf{s}_z := (s_z(1), \dots, s_z(r))^\top$ is the distribution of the initial condition for type z , we first recover the distribution of latent types by averaging-out the initial condition, as in

$$\bar{\boldsymbol{\Lambda}}^\top \boldsymbol{\iota}_r = \Delta_{x_0}^{-1} \boldsymbol{\Lambda}^\top \boldsymbol{\iota}_r = \Delta_{x_0}^{-1} \boldsymbol{\mu} =: \bar{\boldsymbol{\mu}},$$

and then recover the type-specific distributions of the initial condition as

$$\bar{\boldsymbol{\Lambda}} \text{diag}(\bar{\boldsymbol{\mu}})^{-1} = \boldsymbol{\Lambda} \Delta_{x_0} \Delta_{x_0}^{-1} \text{diag}(\boldsymbol{\mu})^{-1} \Delta_{x_0} = \boldsymbol{\Lambda} \text{diag}(\boldsymbol{\mu})^{-1} \Delta_{x_0} = \mathbf{S} \Delta_{x_0} =: \bar{\mathbf{S}},$$

which uses the fact that $\boldsymbol{\Lambda} = \mathbf{S} \text{diag}(\boldsymbol{\mu})$ by definition and $\text{diag}(\bar{\boldsymbol{\mu}}) = \Delta_{x_0}^{-1} \text{diag}(\boldsymbol{\mu}) \Delta_{x_0}$.

We have shown the following result.

Theorem 1. *Let Assumptions 1–3 hold. Then the distributions of the initial condition, s_z , the transition kernels, k_z , and the type probabilities, μ_z , may all be nonparametrically identified, up to a common permutation of the latent types, from the distribution of four consecutive observations.*

Having access to longer time series allows us to weaken Assumption 1. Say that we have access to the joint distribution of X_1, \dots, X_T . Let $\lfloor \cdot \rfloor$ denote the floor function. Redefine the matrix \mathbf{K}_x to let its z -th column be the (vectorized) distribution of $X_{\lfloor T/2 \rfloor + 1}, \dots, X_{T-1}$ given $X_{\lfloor T/2 \rfloor} = x$ and $Z = z$. A typical entry of this matrix in column z has the multiplicative structure

$$k_z(x, x_1) \prod_{i=1}^{\lfloor (T-1)/2 \rfloor - 1} k_z(x_i, x_{i+1})$$

and depends only on the number of time periods involved. Conformably redefine the matrix \mathbf{L}_x so that its z -th column reflects the joint distribution of $X_1, \dots, X_{\lfloor T/2 \rfloor}$ and Z at $X_{\lfloor T/2 \rfloor} = x$ and $Z = z$. Then we can mimic the proof of Theorem 1 with \mathbf{P}_x being the joint distribution of X_1, \dots, X_{T-1} at $X_{\lfloor T/2 \rfloor} = x$ and $\mathbf{P}_{x,x'}$ being the joint distribution of X_1, \dots, X_T at $X_{\lfloor T/2 \rfloor} = x$ and $X_{\lfloor T/2 \rfloor + 1} = x'$, both arranged as two-way tables. Indeed, we again have that

$$\mathbf{P}_x = \mathbf{K}_x \mathbf{L}_x^\top, \quad \mathbf{P}_{x,x'} = \mathbf{K}_{x'} \mathbf{D}_{x,x'} \mathbf{L}_x^\top.$$

Assumption 1 now involves matrices that are of dimension $r^{(T-2)/2} \times r^{(T-2)/2}$ when T is even and of dimension $r^{(T-1)/2} \times r^{(T-3)/2}$ when T is odd. Consequently, we can accommodate up to $r^{(T-2)/2}$ latent types when T is even and $r^{(T-3)/2}$ latent types when T is odd. Assumptions 2 and 3 require no modification.

3 Comparison to prior work

Kasahara and Shimotsu (2009). Identification of mixtures of dynamic discrete choices has previously been considered by Kasahara and Shimotsu (2009). Their Proposition 6 provides an identification result for the matrix of transition probabilities \mathbf{K}_x and the vector of joint probabilities $\boldsymbol{\lambda}_x$ for a *fixed* value x from the joint distribution of six outcomes. The

conditions under which this result is obtained are (in our notation) that (i) the vector λ_x only has positive entries; (ii) there exists a collection of points x_1, \dots, x_{q-1} such that the $q \times q$ matrix \mathbf{M}_x with

$$(\mathbf{M}_x)_{z,i} := \begin{cases} 1 & \text{if } i = 1 \\ k_z(x, x_{i-1}) k_z(x_{i-1}, x) & \text{if } i > 1 \end{cases}$$

is invertible; and (iii) for some x' , $k_z(x, x') > 0$ for all z and $k_z(x, x') \neq k_{z'}(x, x')$ for all $z' \neq z$.

The approach of [Kasahara and Shimotsu \(2009\)](#) is built around the observation that the joint distribution of X_2, X_4, X_6 , conditional on the fact that X_1, X_3, X_6 all take on the value x , factors as a static tri-variate mixture. This argument works around the Markovian dependence, whereas ours exploits it. It also makes clear why they require six time-series observations as opposed to our four.

The difference between the approach of [Kasahara and Shimotsu \(2009\)](#) and ours makes a precise comparison between the requirements underlying them difficult. Still, in the argument of [Kasahara and Shimotsu \(2009\)](#), Conditions (i) and (ii) play a similar role to does our Assumption 1, although we do not require Condition (i) and our techniques avoid the need to work with only a subset of the support points to ensure that the resulting matrix is square. Condition (iii), in turn, is used by [Kasahara and Shimotsu \(2009\)](#) to ensure uniqueness of an eigendecomposition. As such it fulfills the role of our Assumption 2 in their context. Condition (iii) is too strong for that purpose, however. Indeed, a look at their proof shows that their result continues to go through under the weaker requirement that the columns of \mathbf{K}_x are all distinct. This follows from an application of Theorem 6.1 of [De Lathauwer, De Moor and Vandewalle \(2004\)](#) to their set of multilinear restrictions. [Kasahara and Shimotsu \(2009\)](#) have no analog of our Assumption 3 as their argument is for a given value x .

If Conditions (i)–(iii) hold for all x Proposition 6 of [Kasahara and Shimotsu \(2009\)](#) can be applied to each of them. Identification here is up to an arbitrary ordering of the latent types, however, and separate application of their Proposition 6 does not ensure that the same ordering of latent types is recovered in all of the cases. Hence, this argument

only identifies $\mathbf{K}_1\Delta_1, \dots, \mathbf{K}_r\Delta_r$ and $\Delta_1^{-1}\lambda_1, \dots, \Delta_r^{-1}\lambda_r$, where $\Delta_1, \dots, \Delta_r$ are arbitrary permutation matrices. This does not suffice to reconstruct the transition kernels, nor does it lead to identification of the distributions of the initial condition or the distribution of the latent types.

Hu and Shum (2012). In related work, [Hu and Shum \(2012\)](#) entertain a framework where, in addition to the observable variables, the latent types themselves, too, may follow a first-order Markov process. This nests our specification. On the other hand, their approach requires that $r = q$, i.e., that the observable variables cannot take on more values than there are latent types. This is a substantial restriction and is not imposed here.

[Hu and Shum \(2012\)](#) recover the unknown probabilities from the distribution of only four outcomes, as do we. To do so they impose our Assumption 1 together with the requirement that, for each x , there exists an x' and a pair $(x_1, x_2) \neq (x', x)$ such that $k_z(x', x)$, $k_z(x_1, x)$, $k_z(x', x_2)$, and $k_z(x_1, x_2)$ are all strictly positive for all z , and that, in addition, it holds that

$$\frac{k_z(x', x) k_z(x_1, x_2)}{k_z(x', x_2) k_z(x_1, x)} \neq \frac{k_{z'}(x', x) k_{z'}(x_1, x_2)}{k_{z'}(x', x_2) k_{z'}(x_1, x)}$$

for all $z \neq z'$. The first of these two conditions is used to set up a matrix-diagonalization problem. It states that, for every x , there exist two states, x' and x_1 , from which x can be reached by all types, and that there exists another state, x_2 , which is equally reachable from these starting points by all types. Our results here reveal that such restrictions are unnecessary to achieve identification in our setup. The second condition further requires the transition probabilities along these states to be sufficiently different for different latent types. This condition is used by [Hu and Shum \(2012\)](#) to ensure uniqueness (up to scale and permutation) of the eigenvectors in their diagonalization problem. As such, it plays a similar role as our Assumption 2. However, our Assumption 2 is arguably weaker in that it only requires there to exist (collections of) walks along the type-specific Markov chains that occur with different probability for the different types.

Under these conditions, [Hu and Shum \(2012, Lemma 3 and Corollary 2\)](#) establish an analog of [Kasahara and Shimotsu \(2009, Proposition 6\)](#), recovering $\mathbf{K}_1\Delta_1, \dots, \mathbf{K}_r\Delta_r$ and

$\Delta_1^{-1}\lambda_1, \dots, \Delta_r^{-1}\lambda_r$ for unknown permutation matrices $\Delta_1, \dots, \Delta_r$. To be able to proceed further, they additionally assume that, for each x , there exists a functional, say the mean,

$$\delta_{x,z} := \sum_{x'=1}^r k_z(x, x') x',$$

for which it is known that $\delta_{x,1} < \dots < \delta_{x,q}$. This assigns empirical content to the types. Moreover, it allows to recover the matrices $\mathbf{K}_1, \dots, \mathbf{K}_r$ with their columns arranged in a common order, thereby resolving the remaining ambiguity and completing the identification analysis. In principle, and provided the required monotonicity conditions can be found, this can be taken to the data by means of constrained optimization. However, the number of restrictions, $r(q-1)$, may be large, making such a procedure complicated. Furthermore, sampling noise can imply the restrictions to be inconsistent with one another. Our Theorem 1 shows that, under Assumption 3, a common (arbitrary) ordering is identified from the data. Therefore, monotonicity restrictions linking types to outcomes can be dispensed with.¹

4 Estimation

The proof of Theorem 1 is constructive. The key to constructing an estimator based on it is a routine that (approximately) solves the set of equations in (2.3) based on estimators of the matrices on the left-hand side. Such a problem is related to, but different from, joint approximate diagonalization. An algorithm for doing so is provided in a companion paper (Higgins and Jochmans 2021). Alternatively, maximum likelihood estimation is feasible in

¹Hu and Shum (2012, Theorem 1 and Corollary 1) also treat the case where the transition kernels are time dependent. They show that, if five time-series observations are available, their arguments can be used to establish identification of the transition kernels relating time period three to time period four. It turns out that, under their conditions, our techniques can be modified to yield identification of the transition kernel relating time period two to time period three from only four time-series observations. This, then, equally identifies the type-specific marginal distributions of the outcome in those two periods, as well as the distribution of latent types, which does not change with time. Again, this result does not require monotonicity restrictions.

our context. As it is efficient and yields estimated distributions that are easily ensured to satisfy non-negativity and adding-up constraints it carries our preference. A natural way to proceed with implementation is via the EM algorithm ([Dempster, Laird and Rubin 1977](#)).

Likelihood. Let $\mathbf{X} := (X_1, \dots, X_T)$ be a random sequence drawn from the mixture model and let $\mathbf{x} := (x_1, \dots, x_T)$ be a particular realization of this sequence. The probability mass function of \mathbf{X} at \mathbf{x} takes the form

$$\sum_{z=1}^q \mu_z \ell_z(\mathbf{x}; \boldsymbol{\vartheta}_z),$$

where

$$\ell_z(\mathbf{x}; \boldsymbol{\vartheta}_z) := \mathbb{P}(\mathbf{X} = \mathbf{x} | Z = z) = \prod_{x=1}^r s_z(x)^{\{x_1=x\}} \prod_{x'=1}^r k_z(x, x')^{n_{x,x'}(\mathbf{x})}.$$

Here, the $r + r^2$ vector $\boldsymbol{\vartheta}_z$ collects the steady-state distribution s_z and the transition matrix k_z , we use $\{\cdot\}$ to denote the indicator function, and write $n_{x,x'}(\mathbf{x})$ for the number of transitions from x to x' that appear in \mathbf{x} .

The log-likelihood function for a random sample $\mathbf{X}_1, \dots, \mathbf{X}_n$ is

$$\sum_{i=1}^n \log \left(\sum_{z=1}^q \mu_z \ell_z(\mathbf{X}_i; \boldsymbol{\vartheta}_z) \right).$$

Let Z_1, \dots, Z_n denote the (latent) types. The complete-data log-likelihood function equals

$$L_n(\boldsymbol{\Theta}) := \sum_{i=1}^n \sum_{z=1}^q \{Z_i = z\} (\log \mu_z + \log \ell_z(\mathbf{X}_i; \boldsymbol{\vartheta}_z)),$$

where $\boldsymbol{\Theta}$ collects all μ_1, \dots, μ_q and $\boldsymbol{\vartheta}_1, \dots, \boldsymbol{\vartheta}_q$. The EM algorithm iterates on $L_n(\boldsymbol{\Theta})$ and, in our case, is guaranteed to deliver a local maximizer of the log-likelihood ([Wu 1983](#)). We defer to [McLachlan and Krishnan \(2008\)](#) for additional discussion and references on the EM algorithm in a mixture context.

EM iteration. An iteration starting at $\hat{\boldsymbol{\Theta}}$ proceeds as follows. In the E-step we compute the expectation of $L_n(\boldsymbol{\Theta})$ given the data $\mathbf{X}_1, \dots, \mathbf{X}_n$ under the distribution induced by $\hat{\boldsymbol{\Theta}}$. This yields the criterion

$$\mathbb{E}_{\hat{\boldsymbol{\Theta}}}(L_n(\boldsymbol{\Theta}) | \mathbf{X}_1, \dots, \mathbf{X}_n) = \sum_{i=1}^n \sum_{z=1}^q \omega_z(\mathbf{X}_i; \hat{\boldsymbol{\Theta}}) (\log \mu_z + \log \ell_z(\mathbf{X}_i; \boldsymbol{\vartheta}_z)),$$

where

$$\omega_z(\mathbf{X}_i; \hat{\Theta}) := \frac{\hat{\mu}_z \ell_z(\mathbf{X}_i; \hat{\boldsymbol{\vartheta}}_z)}{\sum_{z'} \hat{\mu}_{z'} \ell_{z'}(\mathbf{X}_i; \hat{\boldsymbol{\vartheta}}_{z'})}$$

is the posterior probability that $Z_i = z$. In the M-step we maximize the criterion with respect to Θ to get $\hat{\Theta}$, say. Inspection of $\mathbb{E}_{\hat{\Theta}}(L_n(\Theta) | \mathbf{X}_1, \dots, \mathbf{X}_n)$ reveals that $\hat{\Theta}$ can be written in closed form. With the solution forced to consist of valid probability distributions we find

$$\hat{\mu}_z = \frac{\sum_{i=1}^n \omega_z(\mathbf{X}_i; \hat{\Theta})}{n}$$

and

$$\hat{s}_z(x) = \frac{\sum_{i=1}^n \omega_z(\mathbf{X}_i; \hat{\Theta}) \{X_{i,1} = x\}}{\sum_{i=1}^n \omega_z(\mathbf{X}_i; \hat{\Theta})}, \quad \hat{k}_z(x, x') = \frac{\sum_{i=1}^n \omega_z(\mathbf{X}_i; \hat{\Theta}) n_{x,x'}(\mathbf{X}_i)}{\sum_{x''=1}^r \sum_{i=1}^n \omega_z(\mathbf{X}_i; \hat{\Theta}) n_{x,x''}(\mathbf{X}_i)}.$$

We subsequently replace $\hat{\Theta}$ by $\hat{\Theta}$ and start a new iteration. The procedure is repeated until convergence.

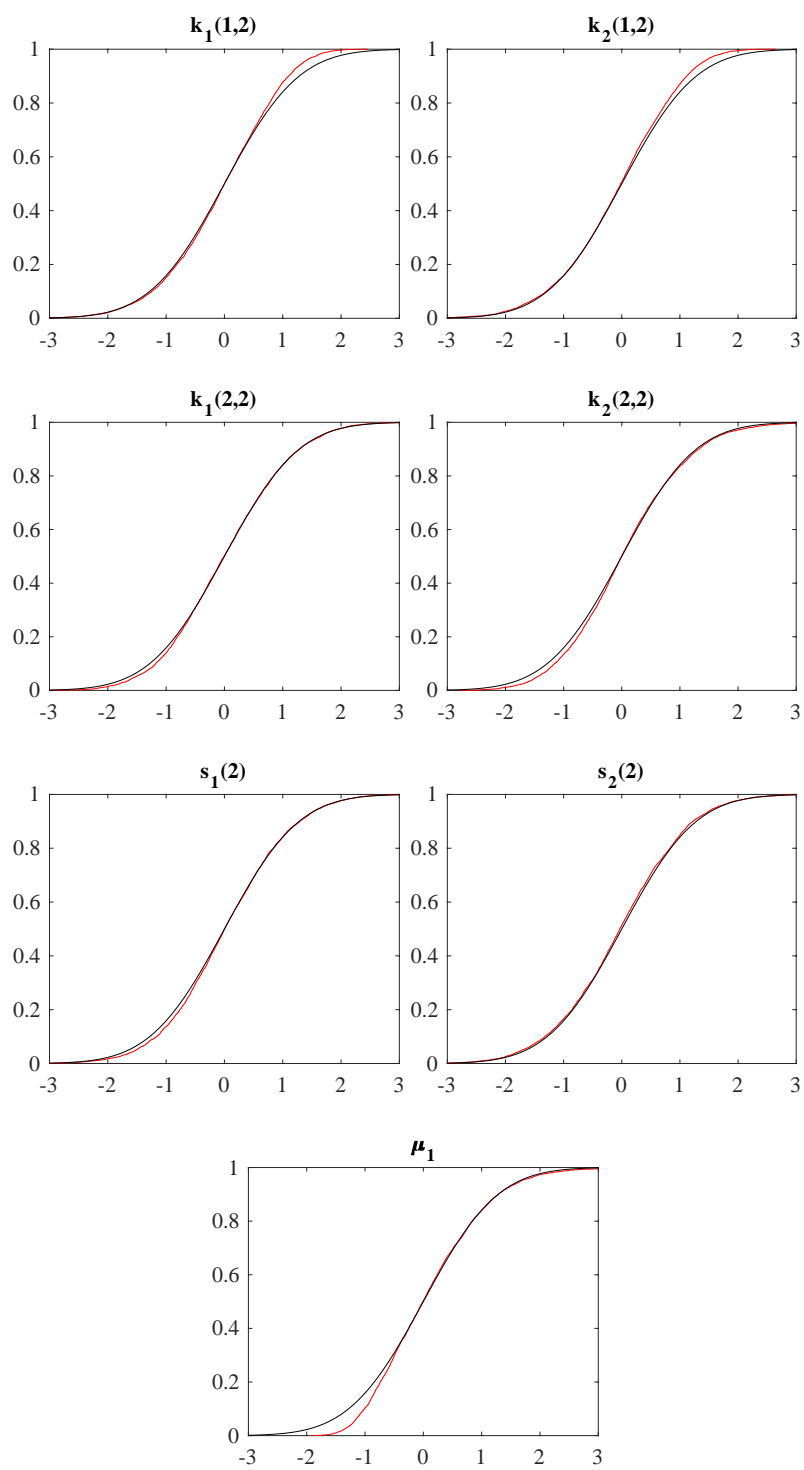
Simulations. We provide results from a Monte Carlo experiment on a two-component mixture of binary decisions. The type-specific transition kernels, k_1 and k_2 , are specified as

k_1	1	2	k_2	1	2
1	2/10	8/10	1	8/10	2/10
2	7/10	3/10	2	3/10	7/10

and we mix the two types with $\mu_1 = 4/10$ and $\mu_2 = 1 - \mu_1 = 6/10$. The type-specific Markov chains are initialized with a draw from their steady-state distributions. In each of 10,000 Monte Carlo replications we estimate the model by maximum likelihood, using the EM algorithm (initiated at a range of different starting values with a terminal condition on the improvement of the likelihood), and estimate the information as the outer-product of the score vector, evaluated at the maximizer.

The plots in Figure 1 contain the empirical cumulative distribution functions (in red) of the Studentized point estimators for the different parameters, obtained from four-wave panel data sets consisting of 500 observations. Each plot also provides the standard-normal

Figure 1: Studentized empirical distributions (red) together with the standard-normal reference distribution (black)



distribution as a benchmark (in black). Overall, the normal approximation performs well. Some deviations can be observed in the upper (lower) tail of the transition probabilities for type 1 (type 2) and in the lower tail of the distribution of the proportion of type 1 individuals. Inspection of the simulation output reveals that these stem from estimation error in the variance. The various parameter estimators are all virtually unbiased. The normal approximation quickly improves as either n grows or as longer panels are considered. We omit additional numerical output.

5 Higher-order Markov dependence

Our argument can be extended to models with higher-order dynamics. To see how this can be done, take a model with second-order Markov dependence. The transition kernel is now

$$k_z(x, x', x'') := \mathbb{P}(X_t = x'' | X_{t-1} = x', X_{t-2} = x, Z = z).$$

For each pair (x, x') , collect the type-specific distributions in the $r \times q$ matrix $\mathbf{K}_{x,x'}$ and, similarly, construct the $r \times q$ matrix $\mathbf{L}_{x,x'}$ as

$$(\mathbf{L}_{x,x'})_{x'',z} := \mathbb{P}(X_3 = x', X_2 = x, X_1 = x'', Z = z).$$

Then

$$\mathbf{P}_{x,x'} = \mathbf{K}_{x,x'} \mathbf{L}_{x,x'}^\top.$$

If we have access to the joint distribution of five observations we can define the collection of matrices

$$(\mathbf{P}_{x,x',x''})_{i,j} := p_{j,x,x',x'',i}$$

in complete analogy to before. We see that

$$\mathbf{P}_{x,x',x''} = \mathbf{K}_{x',x''} \mathbf{D}_{x,x',x''} \mathbf{L}_{x,x'}^\top$$

where, now, $\mathbf{D}_{x,x',x''}$ is the $q \times q$ diagonal matrix that contains the $k_z(x, x', x'')$. The factorizations in the above equations are of the same form as those obtained in Section 2, and the arguments followed there can be modified to apply here.

The general conclusion, then, is that, under suitable modifications of Assumptions 1 to 3, identification of a mixture of Markov processes is possible from the cross-sectional distribution of as little as three effective time-series observations. If dependence is present up to order p , we need $3 + p$ observations. In contrast, an extension of the approach underlying the result in Proposition 6 of Kasahara and Shimotsu (2009) would require $3 + 3p$ observations. An extension of the approach of Hu and Shum (2012) could presumably also be obtained; it would involve $r^2(q - 1)$ monotonicity conditions on the columns of the matrices $\mathbf{K}_{x', x''}$.

Conclusion

We have derived a constructive nonparametric identification result for finite mixtures of dynamic discrete choices. Our method of proof differs from Kasahara and Shimotsu (2009) and Hu and Shum (2012), who rely on arguments from the literature on static mixture models, and is able to deliver full identification without the need to impose monotonicity restrictions. The chief observation behind it is that, while the model implies a collection of multilinear restrictions akin to those used in the analysis of multivariate mixtures, these are only a small subset of the restrictions that arise from the dynamics in the model. This subset of restrictions, in isolation, does not yield identification. The full set of restrictions, however, does.

Our arguments yield identification from three effective time-series observations. Results of Hall and Zhou (2003) and Henry, Kitamura and Salanié (2014) (in a different context) suggest that (point) identification from shorter panels is unlikely to be possible, in general, without imposing additional restrictions. An example of such additional restrictions is given in Gupta, Kumar and Vassilvitskii (2016), where a specific approach to identification of first-order Markov processes from two effective time periods is considered. A necessary (but not sufficient) requirement for their approach to go through is that (in addition to Assumption 1) we have that $r \geq 2q$.

Appendix

Lemma A.1. *Let \mathbf{P} be a permutation matrix and let \mathbf{D} be a diagonal matrix. Then $\mathbf{P}^{-1}\mathbf{D}\mathbf{P}$ is a diagonal matrix.*

Proof. We show that $\mathbf{P}\mathbf{D}\mathbf{P}^{-1}$ is diagonal. Because \mathbf{P} is a permutation matrix, $\mathbf{P}^{-1} = \mathbf{P}^\top$ and so $\mathbf{P}^{-1}\mathbf{D}\mathbf{P} = \mathbf{P}\mathbf{D}\mathbf{P}^{-1}$, from which the result follows. Because \mathbf{P} is a permutation matrix each of its rows and columns contains a single one; the other entries are all zero. Let $\sigma(i)$ be the mapping which yields the column that contains the one in the i -th row and let σ^{-1} be the inverse mapping. Then

$$(\mathbf{P}\mathbf{D})_{i,j} = \sum_k (\mathbf{P})_{i,k} (\mathbf{D})_{k,j} = (\mathbf{P})_{i,j} (\mathbf{D})_{j,j} = \begin{cases} (\mathbf{D})_{\sigma(i),\sigma(i)} & \text{if } j = \sigma(i) \\ 0 & \text{otherwise} \end{cases},$$

where the first equality follows by definition, the second from the fact that \mathbf{D} is diagonal, and the third from the fact that \mathbf{P} is a permutation matrix. Next, using this result yields

$$(\mathbf{P}\mathbf{D}\mathbf{P}^{-1})_{i,j} = (\mathbf{P}\mathbf{D})_{i,\sigma(i)} (\mathbf{P})_{j,\sigma(i)} = \begin{cases} (\mathbf{D})_{\sigma(i),\sigma(i)} & \text{if } j = i \\ 0 & \text{otherwise} \end{cases},$$

so that, indeed, $\mathbf{P}\mathbf{D}\mathbf{P}^{-1}$ is a diagonal matrix. □

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