Predicting Multitasking Abilities from Network-Based Functional Connectivity in Young and Old Adults

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Introduction

- Multitasking, i.e. performing two tasks at once or in close succession, typically induces performance costs on speed and accuracy [1,2]. These costs are often larger in older age [3,4].
- The neural mechanisms behind multitasking costs and their age-related modulation are not yet clear but may be related to the pattern of functional coupling in task-related and -unrelated brain networks [5].

→ Aim: To examine associations between multitasking performance and resting-state functional connectivity (FC) in pre-defined functional networks as well as age modulations thereof using a multivariate out-of-sample prediction approach.

Methods

Participants: **41 young** (21–35 yrs.) and **33 older** (51–71 yrs.) healthy adults

Performance Scores

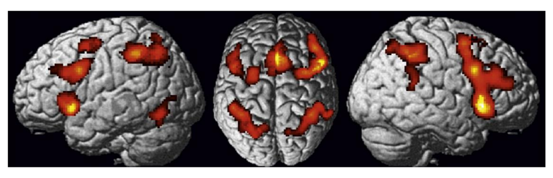
Dual-task costs (DTC) in a psychological refractory period paradigm with speeded tone (Task 1) and letter (Task 2) discrimination of variable temporal overlap (DTC: Task 2 RT difference between 50 and 800 ms overlap)

Global and local task-switching costs in an alternating-runs paradigm with number (Task 1) and letter (Task 2) discrimination (single- and dual-task blocks)

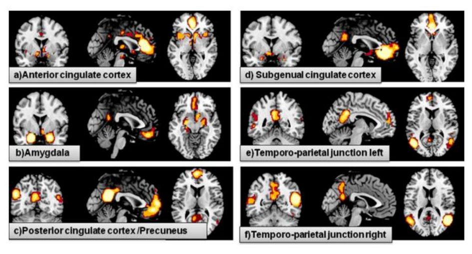
Single-task executive functioning: working memory (Corsi block-tapping) and **inhibitory control** (go/no-go task)

Meta-analytically pre-defined functional networks

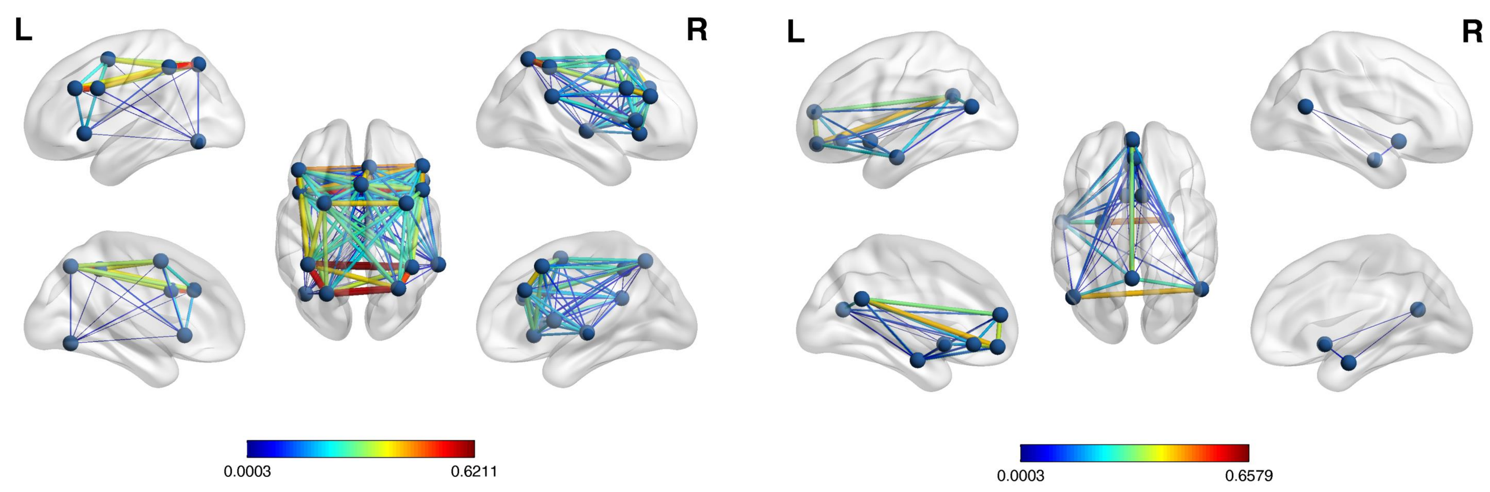
Cognitive Action Control (CogAC) [6]



Extended social-affective default (eSAD) [7]



Within-network FC matrices



RS-fMRI Data Acquisition: Siemens 3 T • 200 T2*-weighted volumes with TR = 2.2 s • eyes closed

Data Analysis

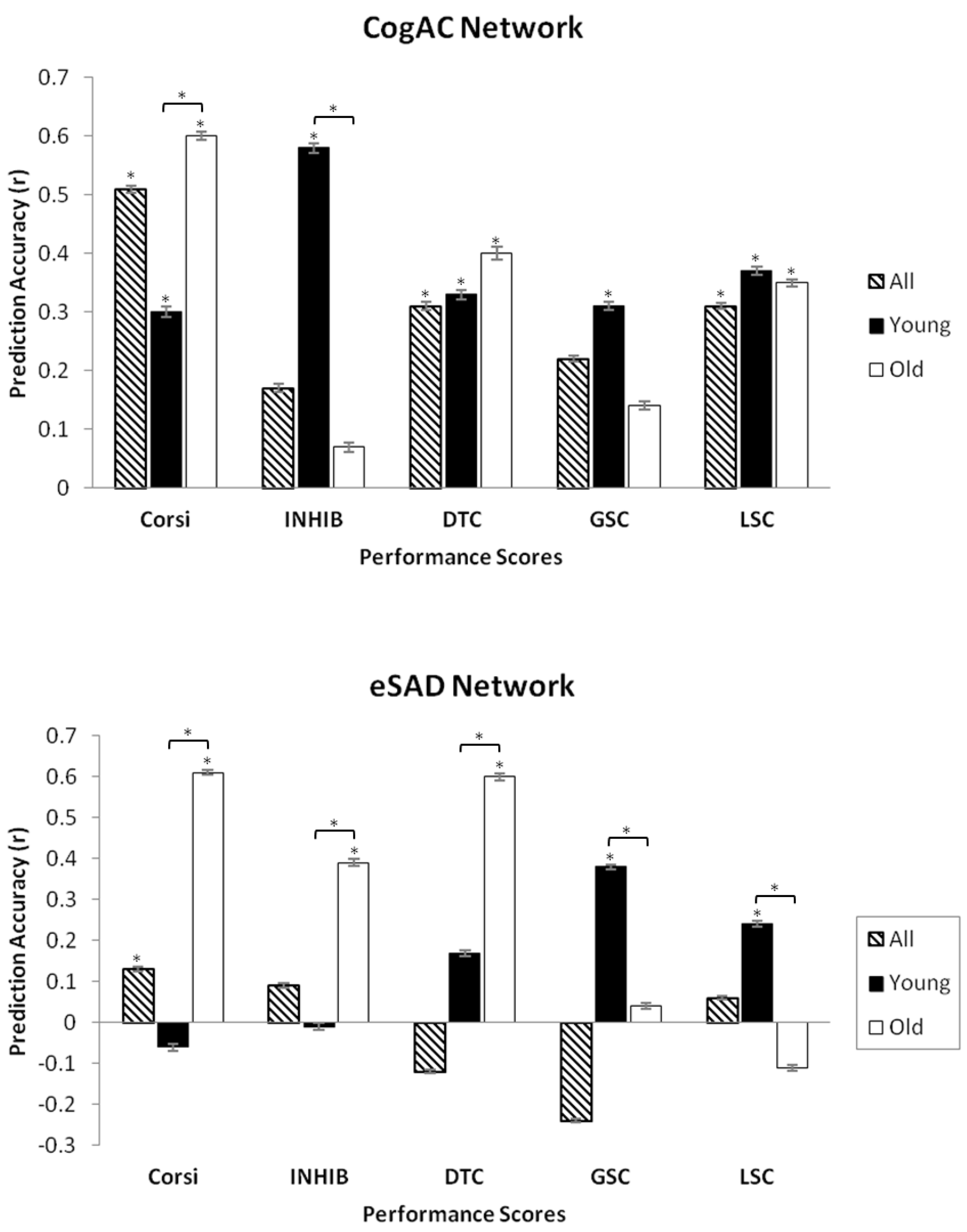
Standard **preprocessing and denoising** [8] using SPM12

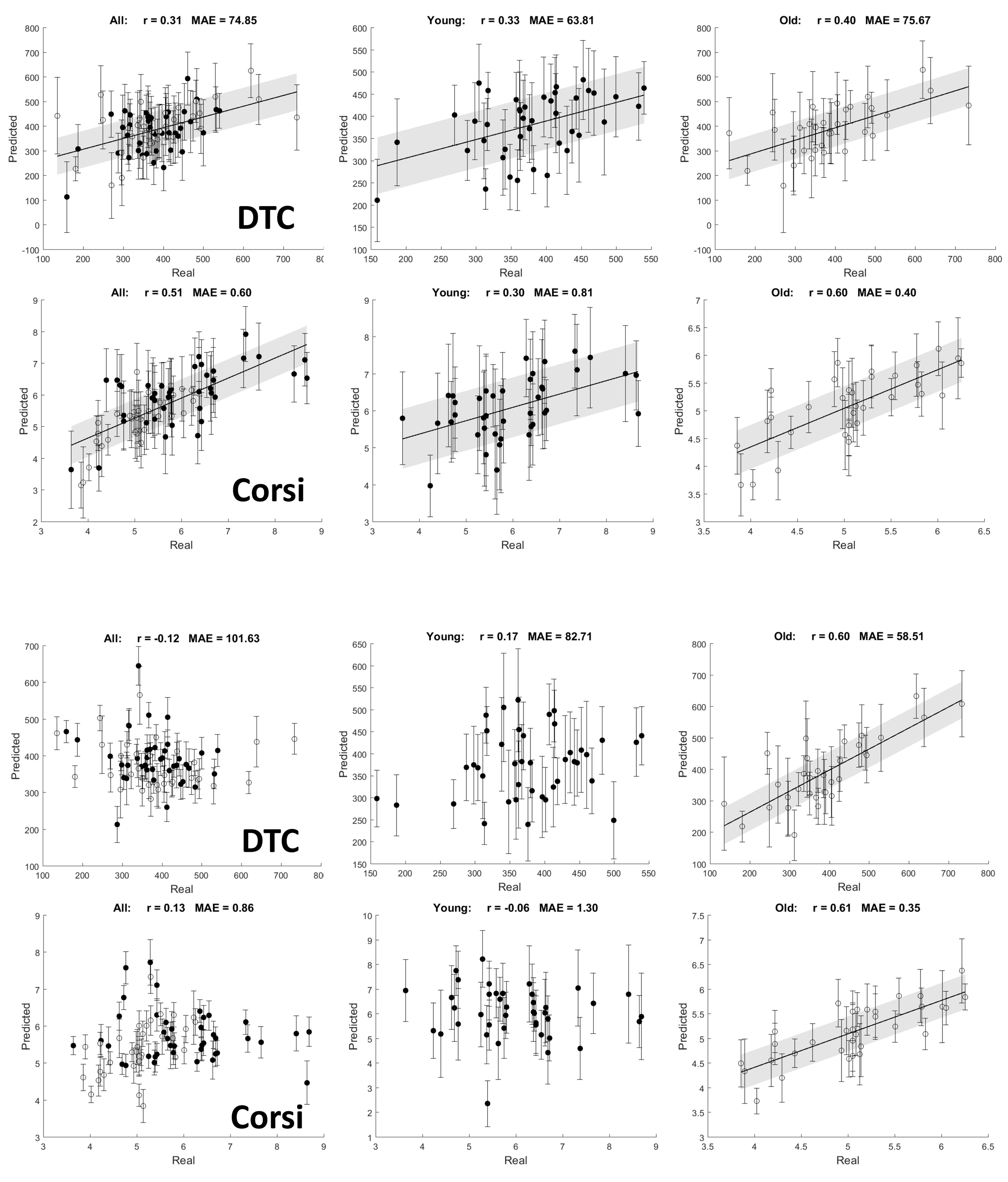
Edgewise FC: Pearson correlation betw/ BOLD-signal time-series **eigenvariates** of each node (6-mm sphere)

Prediction of individual performance based on FC of all edges using **Relevance Vector Machines** [9] with a **10-fold** cross-validation scheme

Accuracy: Pearson correlation betw/ **real and predicted** scores over **250 replications**

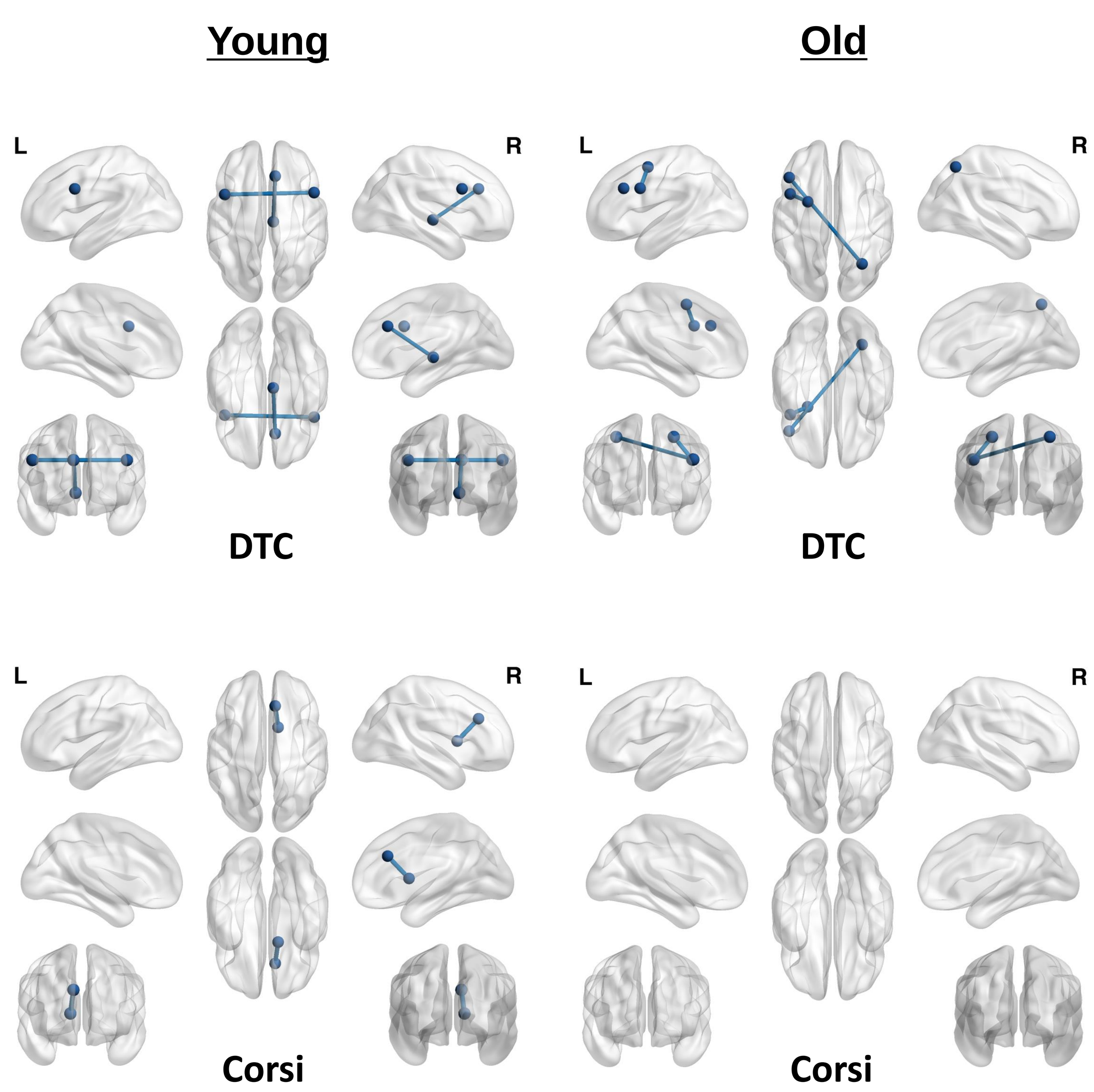
Results





Most consistently used CogAC connections

(≥ 75% non-zero weights across 250 reps)



Discussion

Using a multivariate statistical learning method, multitasking performance and working memory capacity can be predicted at the individual-subject level from resting-state FC in the CogAC network.

→ The CogAC network's FC pattern contains functionally relevant information for multi-tasking and other executive functions.

More consistent predictability in young (vs. older) adults suggests differentiation in the behavioral relevance of this pre-defined multiple-demand network across the lifespan.

The eSAD network, linked to introspection and the default mode of brain function, was not consistently predictive of performance, but its predictiveness showed strong age and task dependence.

→ This age- and task-related specificity in the relevance of the eSAD network's FC for executive functioning possibly reflects life-span changes in the functional architecture and/or in the strategies used for solving such tasks.

CONCLUSIONS:

Out-of-sample performance prediction from network-based resting-state FC is possible, demonstrating

(1) the functional relevance of the pattern of within-network functional coupling at rest;

(2) the benefits of multivariate approaches to sparse but functionally meaningful feature spaces.

Predictability differences attest to the functional specificity of brain networks and corroborate changes in brain–behavior relations with age.

References: [1] Sigman M, Dehaene S (2006) *PLoS Biol*, 4:e220. [2] Pashler H (1994) *Psychol Bull*, 116:220-44. [3] Verhaeghen P, et al. (2003) *Psychol Aging*, 18:443-460. [4] Wasylyshyn C, et al. (2011) *Psychol Aging*, 26:15-20. [5] Langner R, et al. (2015) *Brain Struct Funct*, 220:1739-1757. [6] Cieslik EC, et al. (2015) *Neurosci Biobehav Rev*, 48:22-34. [7] Amft M, et al. (2015) *Brain Struct Funct*, 220:1031-1049. [8] Satterthwaite TD, et al. (2013) *NeuroImage*, 64:240-256. [9] Tipping ME (2001) *J Machine Learn Res*, 1:211-244.

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