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deadleaves: Creating cluttered visual stimuli in Python

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Summary

The Dead Leaves Model (Matheron, 1968) is a stochastic image generation model. The model creates images by sampling objects from a predefined family of distributions. Each object ("leaf") is typically a simple shape, such as a circle or ellipse, and its properties (e.g. position, size, orientation, color) are randomly drawn from these distributions. This sampling process allows precise control over image statistics, which makes it possible to vary or fix specific leaf properties as desired. As a consequence, Dead Leaves Models are widely adopted in the study of image statistics (Lee et al., 2001; Madhusudana et al., 2022; Ruderman, 1997; Zylberberg et al., 2012), visual function (Groen et al., 2012; Maiello et al., 2017; Morimoto et al., 2021; Taylor & Bex, 2015; Wallis & Bex, 2012) and, most recently, as training data for machine learning algorithms (Achddou et al., 2022; Baradad et al., 2021).

Leaves are drawn sequentially onto a two-dimensional canvas from front to back, so later leaves can be partially or fully occluded by earlier ones. This layering reproduces key statistical properties of natural scenes, including occlusion structure, heavy-tailed distributions of contrasts and edges, scale invariance, and higher-order spatial correlations (Lee et al., 2001; Ruderman, 1997). For these reasons, the model serves as an effective null model for studying natural image statistics and early visual processing. Yet, there is no publicly available software yet, which allows users to generate dead leaves images in a standardized way. This is where our package comes in.

`deadleaves` is an open-source Python package which can be used to create dead leaves images in a standardized, yet flexible way. Core functionalities are:

- generating dead leaves images with properties (e.g. sizes, orientations, colors) drawn from a wide range of distributions (e.g. uniform, normal, Poisson, power-law, constant) or directly from an image.
- picking from various leaf shapes (circles, ellipsoids, rectangles, regular polygons).
- sampling in different color spaces (RGB, HSV, grayscale).
- applying different noise or image textures, either to the entire image or per-leaf.
- varying the image area covered by leaves, either by adjusting leaf count (controlling density) or by applying spatial masks to restrict coverage to selected regions.
- creating arbitrarily complex leaf configurations by adding dependencies between leaf features (e.g. space-dependent color gradients).

The package is build around `PyTorch` (Paszke et al., 2017) which allows the use of GPU for a faster sampling process. Users can plug in various distributions for the different model parameters to create a variety of images (Figure 1).

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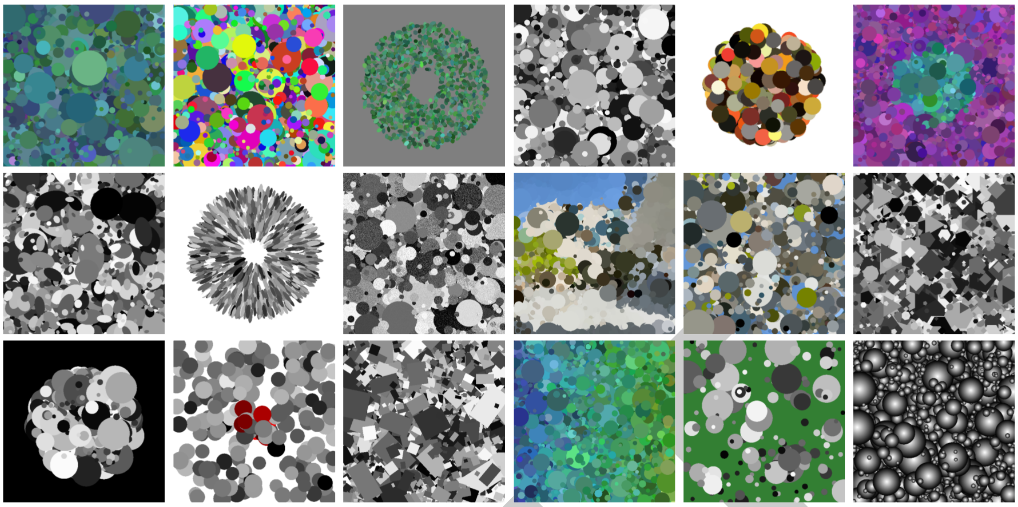

Figure 1: Example images generated with the deadleaves package.

Statement of need

Variations of the Dead Leaves Model have been used for decades to generate images for vision research and computer vision (Baradad et al., 2021; Kaping et al., 2007; Ruderman, 1997; Taylor & Bex, 2015). The model provides a relatively simple way to create complex, cluttered stimuli that match the statistics of natural images or other distributions. Despite its widespread use, there is no standard implementation for generating dead leaves images, and only a few projects have made code publicly available (Baradad et al., 2021). Most researchers therefore implement their own generative code, which is time-consuming, prone to errors, and complicates comparisons across studies (cf. Schmittwilken et al., 2023). Moreover, reproducing existing stimuli is often difficult because the specifications used to generate dead leaves images are often too coarse to fully capture their complexity and stochasticity.

These gaps in standardization and documentation have practical consequences. Small differences in implementation or rendering choices affect the resulting image statistics (Achddou et al., 2022), which are the primary scientific objective in many dead leaves studies. Combined with the stochastic nature of the model, this can make it challenging for researchers to reliably generate stimuli and precisely describe their statistical properties. In short, current practices create barriers to reproducibility and consistent use of dead leaves images.

To address these issues, we developed `deadleaves`, a free and open-source Python package that standardizes dead leaves image generation. The package can be installed via standard package managers or from GitHub. It provides fully parameterized functions for flexible stimulus generation, along with extensive documentation which describes the model, its parameters, and its recommended usage. By simplifying and unifying dead leaves generation, `deadleaves` improves reproducibility, reduces implementation errors, and increases accessibility for both experienced users and newcomers.

State of the field

Dead leaves images have been used across a wide range of disciplines as a controllable, generative model of natural image structure. A central advantage of Dead Leaves Models is that they allow the synthesis of images with certain (naturalistic) statistical properties, while avoiding semantic content and a range of potential biases. Here, we group prior work into three main areas according to the methodological role dead leaves images play.

1. Study of (natural) image statistics

Many studies have used Dead Leaves Models to study and explain statistical regularities commonly observed in natural images by treating them as an analytically tractable model of occlusion-dominated scene structure. A central question is whether the statistical regularities of natural images arise primarily from generic properties of scene composition, rather than from semantic image content.

Early work demonstrated that scale-invariant properties of natural images, most notably the approximate power-law behavior of their power spectra, emerge from scenes composed of objects whose sizes follow a power-law distribution (Ruderman, 1997). Subsequent studies demonstrated that these spectral properties are directly shaped by occlusion, with systematic effects of object overlap, transparency, and opacity (Balboa et al., 2001; Hsiao & Millane, 2005; Zylberberg et al., 2012).

Later work showed that Dead Leaves Models also reproduce other statistical properties of natural scenes – most notably luminance, contrast and other derivative statistics (Lee et al., 2001). This includes the possibility to reproduce statistics characteristic of different scene classes, such as vegetation-like and man-made images (Lee et al., 2001). Extensions of the model with object texture further improved this correspondence (Madhusudana et al., 2022).

Finally, several studies have formalized the relationship between the generative assumptions of the Dead Leaves Model and the resulting image statistics. Analytical derivations link model parameters directly to feature distributions (Pitkow, 2010), and complementary work has established a rigorous mathematical foundation using tools from stochastic geometry and probability theory (Alvarez et al., 1999; Bordenave et al., 2006; Gousseau & Roueff, 2003; Gousseau & Roueff, 2007).

2. Visual psychophysics

In visual psychophysics, dead leaves images are primarily used as controlled stimuli that preserve selected statistical properties of natural scenes while minimizing semantic content. This allows researchers to study perceptual sensitivity to specific image statistics and specific visual features in isolation. For example, dead leaves stimuli have been used to investigate the conditions under which surfaces appear self-luminous, by carefully controlling luminance and color distributions (Morimoto et al., 2021).

A different line of research uses dead leaves stimuli to study rapid scene categorization under controlled image statistics. By manipulating orientation and spatial frequency content, dead leaves images have been used in adaptation paradigms to probe which image statistics support rapid scene-level judgments (Kaping et al., 2007), while contrast and higher-order statistics derived from dead leaves images have been directly controlled in categorization tasks to isolate their contribution to rapid scene processing (Groen et al., 2012).

Finally, dead leaves images have been modified to selectively target specific perceptual cues while maintaining global image structure. Spatially localized or object-level blur has been introduced to study blur detection and discrimination (Maiello et al., 2017; Taylor & Bex, 2015), and dead leaves patterns have been embedded into natural images to study visual crowding while preserving control over local image statistics (Wallis & Bex, 2012).

Across these applications, Dead Leaves Models function as semantically neutral, yet statistically structured stimuli that enable precise manipulation of image properties (such as size, contrast, color, and texture) relevant to human visual perception.

3. Synthetic data for computer vision

Dead Leaves Models have recently been used to generate synthetic images with fully controlled statistical and generative structure, providing training and evaluation data for computer vision tasks and models.

One application is in training computer vision models on synthetic data that bypasses costly real-image collection. Dead leaves images have been used for tasks such as disparity estimation (Madhusudana et al., 2022), learning visual representations that emphasize shape and occlusion cues (Baradad et al., 2021), and image restoration including denoising and deblurring (Achddou et al., 2022).

Beyond training neural networks, dead leaves images have also been used as a benchmark for evaluating image quality, for example in assessing texture reproduction on digital cameras (Cao et al., 2010).

Overall, these applications illustrate that Dead Leaves Models provide a flexible tool for generating semantically neutral yet statistically structured images, bridging the gap between highly simplified synthetic stimuli and the complexity of natural scenes.

Software Design

`deadleaves` is an object-oriented framework for generating dead leaves images. The package is organized around four core classes that separate: (1) sampling leaf geometry, (2) sampling leaf appearance parameters, (3) rendering the dead leaves image, and (4) performing advanced manipulations of individual leaf parameters without resampling the entire scene.

The geometric structure in the Dead Leaves Model is generated through an iterative sampling procedure. At each iteration i, a position (x_i, y_i) is drawn uniformly from the canvas and shape parameters (e.g., size and orientation) are sampled to define a leaf L_i. Pixels not yet assigned to a leaf and covered by L_i are labeled with index i, effectively layering leaves from front to back. The process continues until a stopping criterion is met: either a fixed number of leaves has been sampled or a target area has been filled, which could either be the entire canvas or a specified region.

The geometry stage produces two outputs: (a) a `leaf_table` in the form of a pandas DataFrame, which contains the sampled geometric parameters of all leaves (position, shape, size, etc), and (b) a `segmentation_map` in which each pixel is either labeled with its corresponding leaf index i or labeled as background.

Leaf appearance is assigned independently of geometry by sampling color parameters and, optionally, texture parameters for each leaf from user-defined distributions. These appearance parameters are stored alongside the geometric parameters in the `leaf_table`, and can be defined in a range of color spaces, such as RGB, HSV, or grayscale. This separation allows geometry, color, and texture to be manipulated independently, enabling controlled experiments that disentangle their respective contributions.

The rendering class takes the `leaf_table` and, if available, the `segmentation_map`, and colors the canvas pixels according to the stored appearance parameters, optionally adding leaf-specific texture. It can also add global noise or texture across the entire image that is not tied to individual leaves. If no `segmentation_map` is provided, it is generated automatically from the geometric parameters in the `leaf_table`. Because rendering is directly tied to the segmentation map, the image has pixel-accurate boundaries with sharp edges. This can be particularly useful for segmentation tasks, where blur-based rendering can make object boundaries less defined.

Because sampling and rendering are decoupled, leaf parameters can be modified after the initial sampling step and the scene can be re-rendered without regenerating the full geometry. This enables operations such as adding motion to leaves, interpolating between parameter sets, or composing scenes from different distributions, e.g. by placing a proto-object onto a leaf background (see examples in Figure 1). A dedicated class supports these workflows by allowing multiple `leaf_tables` to be merged, `segmentation_maps` to be regenerated, and leaf indices (i.e. leaf layering) to be manipulated, providing more control over the final scene.

The current renderer focuses on exact compositions and does not implement effects such as blur or transparency yet. However, the class design is intentionally modular: geometry, appearance, and rendering are implemented as interchangeable classes. This makes it straightforward to extend the framework with new leaf shapes, color models, sampling distributions, or rendering methods (e.g., transparency-aware compositing) without changing the core pipeline. Because most classes exchange data through the `leaf_table` (a pandas DataFrame), additional features such as transparency or blur can be added independently of the existing components.

Research Impact Statement

The `deadleaves` package provides a user-friendly, well-documented framework for generating a wide range of dead leaves images, including many stimuli which have been used in prior work. Since the Dead leaves Model has been a standard tool in research for decades, we expect the package to support further research in visual neuroscience and machine learning. In addition, we think that it allows for new applications in e.g. neurophysiology or aesthetics research.

AI usage disclosure

ChatGPT 5 (OpenAI, 2025-26) was used to assist in improving code, documentation, and typesetting, and for generating test cases for package components. No AI content was used directly. All suggestions were manually adapted to ensure correctness and fit the intended context.

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