

# HW8

June 2, 2025

## 0.0.1 3. Experimental Comparison: ISTA vs FISTA

(a) **Fixed Step Size** From the results:

- **ISTA (fixed)** took **1.6203 s** and **23,275 iterations**
- **FISTA (fixed)** took only **0.1200 s** and **1,000 iterations**

We observe that **FISTA converges significantly faster** than ISTA when using a fixed step size, both in terms of iteration count and wall-clock time.

(b) **Backtracking Line Search**

- **ISTA (backtracking)**: **3.2280 s**, **5,851 iterations**
- **FISTA (backtracking)**: **0.1718 s**, **1,170 iterations**

Even with backtracking, **FISTA outperforms ISTA**. While backtracking reduces the number of iterations required by ISTA (compared to fixed step), it increases the per-iteration cost. FISTA still achieves the target accuracy in fewer iterations and in less time.

**Conclusion** Across both settings, **FISTA is clearly faster** and more efficient than ISTA. This advantage holds whether we use a fixed step size or backtracking line search. FISTA's theoretical acceleration translates into substantial practical gains. Backtracking is slower for both cases, probably because we are checking for more stuff.

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[1]: import numpy as np
import matplotlib.pyplot as plt
import time

# 1) Data generation for Problem 1
m, n, s = 300, 500, 2
np.random.seed(0)

#  $A \in \mathbb{R}^{m \times n}$ , sparse  $x_*$  with  $s=2$  nonzeros of size  $\sim 100$ 
A = np.random.randn(m, n)
x_star = np.zeros(n)
p = np.random.permutation(n)
x_star[p[:s]] = 100 * np.random.randn(s)
b = A.dot(x_star)

= 1.0 # LASSO weight
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# smooth part  $g(x) = \|Ax - b\|_2^2$ 
def g(x):
    return np.linalg.norm(A.dot(x) - b) ** 2

# full LASSO objective  $f(x) = g(x) + \|x\|_1$ 
def objective(x):
    return g(x) + * np.linalg.norm(x, 1)

# Soft-thresholding operator:  $\text{prox}_{\{\}}(\cdot)$ 
def soft_threshold(z, lam):
    return np.sign(z) * np.maximum(np.abs(z) - lam, 0.0)

# 2) ISTA with fixed step-size
def ista_fixed(A, b, , x0, eps, max_iter=10**6):
    x = x0.copy()
    f_star = objective(x_star)
    L = 2 * np.linalg.norm(A, 2)**2          # Lipschitz of  $g(x)$ 
    t = 1.0 / L                               # fixed step =  $1/L$ 
    errors, f_diffs = [], []
    t_start = time.time()

    for k in range(1, max_iter + 1):
        # 1) gradient of  $g$  at  $x$ 
        grad = 2 * A.T.dot(A.dot(x) - b)
        # 2) ISTA update:  $x \leftarrow \text{soft\_threshold}(x - t \text{ grad}, t)$ 
        x = soft_threshold(x - t * grad, t * )

        # 3) track relative error
        rel_err = np.linalg.norm(x - x_star) / np.linalg.norm(x_star)
        errors.append(rel_err)
        f_diffs.append(objective(x) - f_star)
        if rel_err < eps:
            break

    total_time = time.time() - t_start
    return x, errors, f_diffs, total_time

# 3) ISTA with backtracking line-search
def ista_backtracking(A, b, , x0, eps, max_iter=10**6, t_init=1.0, beta=0.5):
    x = x0.copy()
    f_star = objective(x_star)
    errors, f_diffs = [], []
    t_start = time.time()

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for k in range(1, max_iter + 1):
    grad = 2 * A.T.dot(A.dot(x) - b)
    t = t_init

    # Backtracking loop: find t so that
    #  $g(x_{\text{new}}) \leq g(x) + g(x)^T (x_{\text{new}} - x) + (1/(2t)) \|x_{\text{new}} - x\|^2$ 
    while True:
        # candidate  $x_{\text{new}}$  via prox step
        x_new = soft_threshold(x - t * grad, t * )
        lhs = g(x_new)
        diff = x_new - x
        rhs = (
            g(x)
            + grad.dot(diff)
            + 0.5 * (1.0 / t) * np.linalg.norm(diff)**2
        )
        if lhs <= rhs:
            break
        t *= beta

    x = x_new
    rel_err = np.linalg.norm(x - x_star) / np.linalg.norm(x_star)
    errors.append(rel_err)
    f_diffs.append(objective(x) - f_star)
    if rel_err < eps:
        break

total_time = time.time() - t_start
return x, errors, f_diffs, total_time

# 4) FISTA with fixed step-size
def fista_fixed(A, b, x0, eps, max_iter=10**6):
    x_old = x0.copy() #  $\tilde{x}^{k-1}$ 
    x = x0.copy() #  $\tilde{x}^k$ 
    f_star = objective(x_star)
    L = 2 * np.linalg.norm(A, 2)**2
    t = 1.0 / L

    errors, f_diffs = [], []
    t_start = time.time()

    for k in range(1, max_iter + 1):
        if k == 1:
            y = x
        else:
            # momentum step:  $y = \tilde{x}^k + ((k-2)/(k+1)) (\tilde{x}^k - \tilde{x}^{k-1})$ 

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        y = x + ((k - 2) / (k + 1)) * (x - x_old)

        grad_y = 2 * A.T.dot(A.dot(y) - b)
        x_new = soft_threshold(y - t * grad_y, t * )

        x_old = x
        x = x_new

        rel_err = np.linalg.norm(x - x_star) / np.linalg.norm(x_star)
        errors.append(rel_err)
        f_diffs.append(objective(x) - f_star)
        if rel_err < eps:
            break

    total_time = time.time() - t_start
    return x, errors, f_diffs, total_time

# 5) FISTA with backtracking line-search
def fista_backtracking(A, b, , x0, eps, max_iter=10**6, t_init=1.0, beta=0.5):
    x_old = x0.copy()
    x = x0.copy()
    f_star = objective(x_star)
    t = t_init

    errors, f_diffs = [], []
    t_start = time.time()

    for k in range(1, max_iter + 1):
        if k == 1:
            y = x
        else:
            # momentum:  $y = x^k + ((k-2)/(k+1))(x^k - x^{k-1})$ 
            y = x + ((k - 2) / (k + 1)) * (x - x_old)

        grad_y = 2 * A.T.dot(A.dot(y) - b)
        t_k = t

        # Backtracking: find  $t_k$  so that
        #  $g(x_{new}) \leq g(y) + g(y)^T (x_{new} - y) + (1/(2 t_k)) \|x_{new} - y\|^2$ 
        while True:
            x_temp = soft_threshold(y - t_k * grad_y, t_k * )
            lhs = g(x_temp)
            diff = x_temp - y
            rhs = (
                g(y)
                + grad_y.dot(diff)

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        + 0.5 * (1.0 / t_k) * np.linalg.norm(diff) ** 2
    )
    if lhs <= rhs:
        break
    t_k *= beta

    x_old = x
    x = x_temp
    t = t_k # carry forward this t_k for the next iteration

    rel_err = np.linalg.norm(x - x_star) / np.linalg.norm(x_star)
    errors.append(rel_err)
    f_diffs.append(objective(x) - f_star)
    if rel_err < eps:
        break

    total_time = time.time() - t_start
    return x, errors, f_diffs, total_time

# 6) Run all four methods ( = 1e-3)
eps = 1e-3
x0 = np.zeros(n)

x_if, err_if, f_if, t_if = ista_fixed(A, b, , x0, eps)
x_ib, err_ib, f_ib, t_ib = ista_backtracking(A, b, , x0, eps)

x_ff, err_ff, f_ff, t_ff = fista_fixed(A, b, , x0, eps)
x_fb, err_fb, f_fb, t_fb = fista_backtracking(A, b, , x0, eps)

results = {
    'ISTA_fixed': {'time': t_if, 'errors': err_if},
    'ISTA_back': {'time': t_ib, 'errors': err_ib},
    'FISTA_fixed': {'time': t_ff, 'errors': err_ff},
    'FISTA_back': {'time': t_fb, 'errors': err_fb},
}

# 7) Plot convergence curves
plt.figure(figsize=(8, 5))
for label, data in results.items():
    iters = len(data['errors'])
    # approximate cumulative time (uniform distribution over iterations)
    if iters > 0:
        t_cumsum = np.cumsum([data['time'] / iters] * iters)
        plt.semilogy(t_cumsum, data['errors'], label=label)

plt.xlabel('Time (s)')

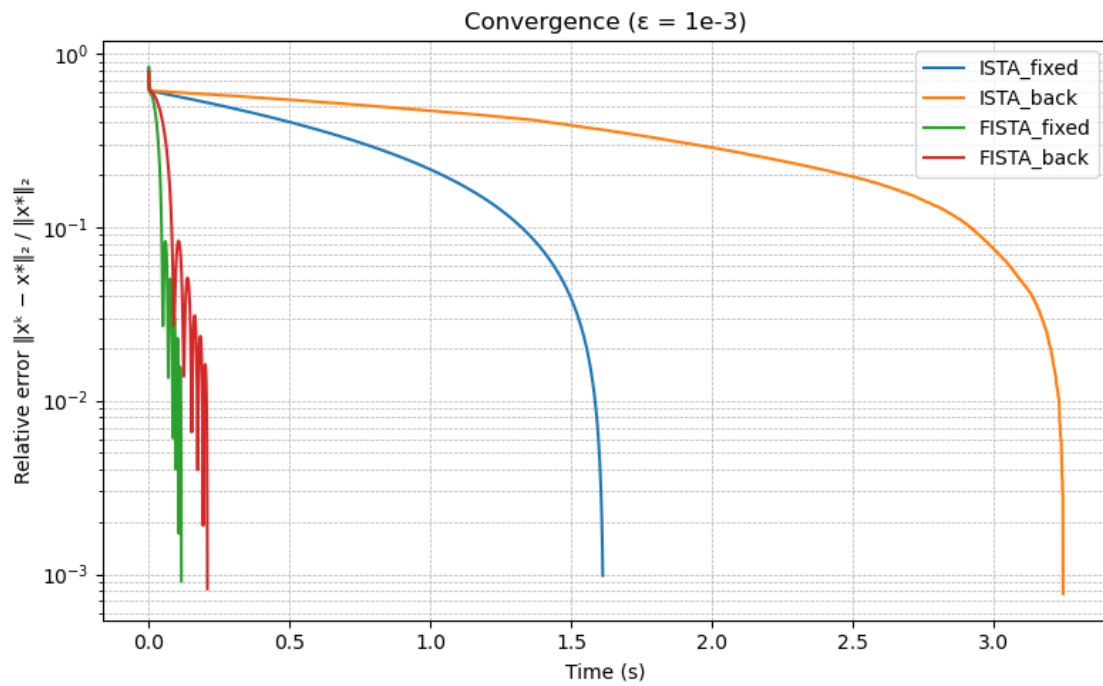
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plt.ylabel('Relative error  $\|x - x^*\| / \|x^*\|$  ')
plt.title('Convergence ( $\epsilon = 1e-3$ )')
plt.legend()
plt.grid(True, which='both', ls='--', lw=0.5)
plt.tight_layout()
plt.show()

# 8) Print a brief summary
for label, data in results.items():
    print(f"{label:12s} → Time: {data['time']:.4f} s, Iterations: {len(data['errors'])}")

```



```

ISTA_fixed      → Time: 1.6125 s, Iterations: 23275
ISTA_back       → Time: 3.2472 s, Iterations: 5851
FISTA_fixed     → Time: 0.1161 s, Iterations: 1000
FISTA_back      → Time: 0.2084 s, Iterations: 1170

```